

# DL-based Optical Fibre Fault Detection for Healthcare Telesurgery Communication System

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**Abstract**—Telesurgery is one of the fastest growing fields in healthcare where surgeons are able to perform operations remotely through controllers by using robots connected to a high-speed network. Optical fibers are heavily utilized in this process due to the fact that the bandwidth is high, the latency rates low, essentially supporting active real-time data transfer as well as control. However, faults with optical fibers can be problematic at times, causing delays which compromises on the precision and safety of surgeries. This paper presents a DL-based framework for detecting faults and enhancing optical fiber communication in telesurgery. We used deep learning (DL) models like Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU), and Long Short-Term Memory (LSTM) to identify these faults from Optical Time-Domain Reflectometer (OTDR) traces. Our models are trained using optimizers like Adam, Nadam, and RMSprop. Among these, LSTM proves to be the most effective, achieving the highest accuracy in fault detection. We also integrated real-time fault detection along with monitoring delays in communication. This innovation ensures that surgical operations can proceed smoothly and accurately.

**Index Terms**—Telesurgery, Optical Fibres, Fault detection, Communication, Deep Learning, Artificial intelligence

## I. INTRODUCTION

Healthcare is one of the most important leading sectors of any country. Proper healthcare is essential to every being, helping maintain good health and carrying out complex surgeries to maintain the proper working of the human body. One of the recent developments in healthcare is telemedicine. Telemedicine, or e-medicine, is the remote delivery of medical services across an infrastructure. This includes communicating electronic information over the network to access and monitor patient data records across distances and providing accessible healthcare services. Telemedicine has various applications such as video consultations and improving patient outcomes. Thus, telemedicine saves both the patients' and the health care provider's time and the cost of the treatment. With telemedicine comes the component of Telesurgery under it. Telesurgery is the process of performing surgeries that are performed remotely by a surgeon and robot using high-speed communication networks. Telesurgery helps

in doing surgeries on time with no time lag. Telesurgery efficiently eliminates geographical boundaries and functions, allowing faster recovery and increased surgical precision.

Optical fibre networks are preferred for their high bandwidth and low latency, making them ideal for transmitting the large amounts of data required for real-time surgical procedures. Telecommunication is vital in telesurgery because light-carrying optical fibres link quickly to the remote surgery area. Real-time interaction and accurate communication occur through these fibres transfer high-definition video, and precise control signals. It allows surgeons to perform surgeries from the comfort of their offices hundreds of kilometres away from the patient, giving people in remote and understaffed hospitals a chance to receive treatment from a specialist. Due to the importance of optical fibres in creating stable and secure communication that is vital to the success of telesurgery, its reliability and efficiency are critical issues. In addition, the reliability of the telesurgery is further complemented by the redundancy encompassed by the optical fibre systems. If there is a problem with communication, having multiple optical fibre lines helps to get connections that will enable the surgeries to go on. [1] reflected on the first experiment done via high communication optical fibres and robotic telesurgery in California. The model performed a biopsy and a surgical operation laparoscopy, which was successful. The emphasis on network communication for enhancing surgical capabilities was also done in [2]. In [3], the authors used optical fibres and bend-enhanced fibre (BEF) sensors to improve the teleoperation of a small mobile robot responsible for instrumenting joint angles.

These faults in the fibres can create service disruption that threatens patient safety and surgery success, among other risks. The use of artificial intelligence in fault detection systems has completely changed how these faults from optical fibre communication systems are detected and diagnosed. With the help of advanced deep learning techniques, these systems could consistently analyse the

state of the optical fibre network to detect signs of early degradation or a fault that might be heading our way. Entering this real-time monitoring, losses and other issues like signal loss, attenuation, or even damage to the fibres can easily be detected. When a fault is passed to the system, the artificial intelligence (AI) system can provide technicians early notice. This will disrupt the entire backbone of the communication network., the system can automatically redirect the data stream through other paths, ensuring continuous communication without interfering with the surgical procedure.

An advantage of fault detection based on AI is that such a system can improve upon previous results based on fault data collected over time. With the data containing various fault scenarios, an AI systems can learn normal operational parameters and distinguish faults at first sight. This is also important to guarantee reliance on telesurgery operations. Such proactive fault management ensures that the requirements of fast and low latency communication links for telesurgery, which are crucial for real-time data transmission and control, are maintained to meet the precision and reliability of telesurgery. The appropriateness of AI techniques in telesurgery increases with developments in the sector, and counteracting the problems that come with optical fibre communication will be essential to enhance surgery benefits to the consumer.

In [4], an innovative blockchain-driven framework was employed to curb the malicious data entering 6G communication channels using the Real-Or-Random Oracle (ROR) model and Scyther simulation tool. The model outperformed the current existing approaches. The authors proposed the Fuzzy Logic Trust-Based Access Control Algorithm (FL-TACA) in [5], which helps secure communication in telerobotics, ensuring effectiveness in patient care and providing data security and reliability. To mitigate communication delays in rural areas, a semi-autonomous system was developed [6], which implements subtasks individually with fluid-submerged peg transfer (resembling bleeding events) and surgical debridement. The systems showed robustness with a performance rate of 87% and reduced completion time delays. The paper [7] proposes a machine learning framework for anomaly detection in optical fibre monitoring, utilizing an autoencoder for fault detection and an attention-based bidirectional GRU for fault localization done via OTDR processing, showing significant improvements in fault detection.

The authors in [8], highlights the importance of telesurgery in remote locations with high-speed data transfer and proposed an architecture that shows Tactile Internet as a network backbone which encourages faster response time using 5G enabled networks. An intelligent blockchain-based TS framework was proposed in [9], incorporating AI algorithms to train surgical robots. The 6G communication channel helps mitigate latency issues while exchanging commands, and the data storage problem is curbed using the InterPlanetary File System (IPFS) protocol. A framework named HaBiTs was proposed in [10] in which security is

achieved via Smart Contracts.

### A. Research Contributions

The significant contributions of this article are as follows.

- We proposed a DL-based framework that significantly improves the accuracy of fault detection in optical fibers and helps in enhancing the reliability of communication in telesurgery systems.
- We performed a comparative analysis of various deep learning architectures (RNN, GRU, LSTM) and optimizers (Adam, NAdam, RMSprop), demonstrating their impact on model performance.
- Further, the proposed framework is evaluated through various performance metrics such as accuracy, loss, precision, recall, F1-score and ROC.

### B. Paper Outline

The rest of the paper is organized as follows. The system model and problem formulation is elucidated in section II. The proposed framework is shown in section III. Results are shown in section IV. The section V presents the conclusion and future work.

## II. SYSTEM MODEL AND PROBLEM FORMULATION

The system model is designed to enhance the reliability of communication between a surgeon and a robotic system in telesurgery by utilizing Deep Learning (DL) to detect faults in optical fibers. The system uses OTDR for real-time monitoring of optical fibers by analysing reflected light signals, identifying and classifying potential faults in the communication channel.

To check how well this system is working, we look at the accuracy metric  $\Psi$ , which is defined as:

$$\Psi = \frac{1}{N} \sum_{i=1}^N \delta(\hat{y}_i, y_i) \quad (1)$$

In this equation,  $N$  is the total number of samples the system uses for fault detection. Each sample is labeled with a predicted fault label  $\hat{y}_i$  and a true fault label  $y_i$ . The  $\delta(\hat{y}_i, y_i)$  is an indicator function. It gives output 1 if  $\hat{y}_i$  matches  $y_i$ , and 0 if they don't match. By making  $\Psi$  as accurate as possible, the system tries to detect and classify optical fiber faults with minimal error. This helps to quickly find any problems with the communication link. Quickly spotting these issues can make a big difference when surgical teams talk to robotic systems during telesurgery. The accuracy of this metric is really important for keeping the system reliable and safe because if there's a fault, it could mess up communication and put surgery at risk. Thus, effective fault detection is key for keeping telesurgery systems reliable and safe. By finding faults in the optical fibers accurately, the AI system can help timely fix issues that might happen. This prevents communication failures that could impact the surgical success.

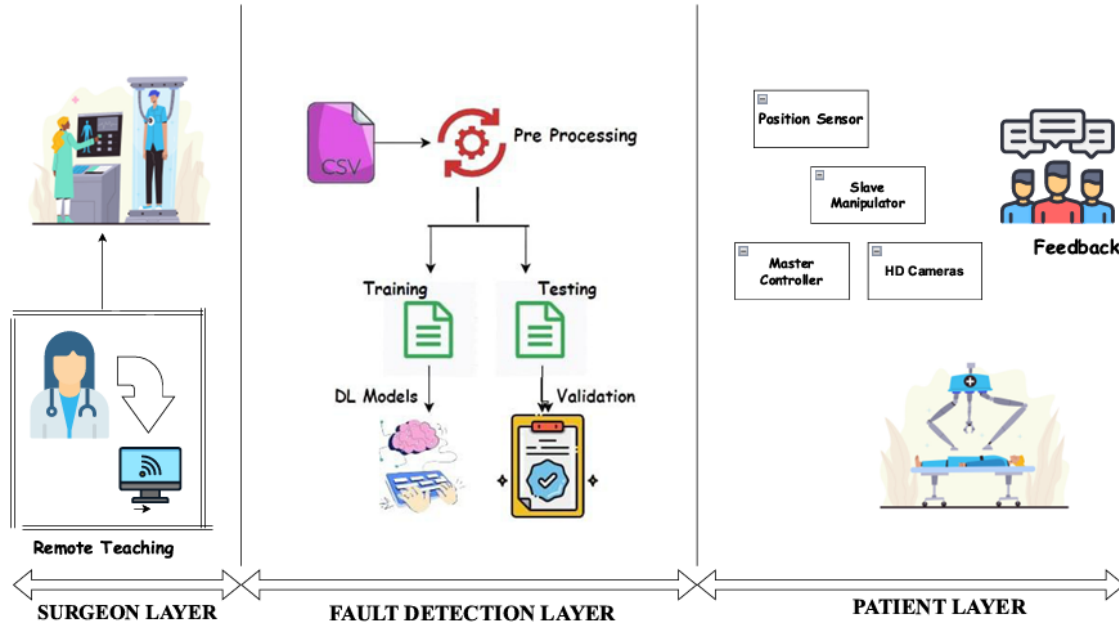


Fig. 1: Proposed framework

### III. PROPOSED FRAMEWORK

The proposed framework (as shown in Fig. 1) consists of three subsections: the surgeon layer, fault detection layer, and patient layer. Each layer is described as follows.

#### A. Surgeon Layer

In telesurgery, effective communication between the surgeon and the robotic system is really important. This communication helps make sure surgeries are done accurately and safely. Optical fibers play a key role here by allowing for fast data transfer that's needed for real-time operation. However, if there's a fault with the optical fibers, it can slow things down a lot, which impacts the overall system performance.

The command accuracy  $A_s(t)$  is a critical metric for evaluating how well the robotic system's responses align with the surgeon's commands. This accuracy is given by:

$$A_s(t) = \frac{|R(t) - C(t)|}{|C(t)|} + \delta(t) \quad (2)$$

where  $R(t)$  represents the actual response of the system,  $C(t)$  denotes the command issued by the surgeon, and  $\delta(t)$  accounts for any dynamic errors or noise in the system. Achieving a high command accuracy is essential for ensuring the precision of the telesurgical operations.

The total communication delay  $T_d(t)$  in the system encompasses several components: the processing delay  $\tau_{\text{proc}}(t)$ , network transmission delays  $\tau_{\text{net}}(t)$ , and delays introduced by optical fiber faults  $\tau_{\text{fault}}(t)$ , along with any noise and jitter  $\epsilon(t)$ . This can be expressed as:

$$T_d(t) = \tau_{\text{proc}}(t) + \tau_{\text{net}}(t) + \tau_{\text{fault}}(t) + \epsilon(t) \quad (3)$$

The delay due to faults in optical fibers can be modeled by:

$$\tau_{\text{fault}}(t) = \frac{L_f \cdot \alpha_f(t)}{c_f} \left( 1 + \frac{\beta_f \cdot d_f(t)}{L_f} \right) \quad (4)$$

where  $L_f$  is the fiber length,  $\alpha_f(t)$  represents the time-varying severity of the fault,  $c_f$  is the speed of light in the fiber,  $\beta_f$  is a coefficient representing the impact of the fault, and  $d_f(t)$  is the distance affected by the fault.

Furthermore, the cumulative impact of multiple faults on communication delay is given by:

$$\Delta T_{\text{cum}} = \sum_{i=1}^N \frac{L_{f,i} \cdot \alpha_{f,i}(t)}{c_f} \left( 1 + \frac{\beta_{f,i} \cdot d_{f,i}(t)}{L_{f,i}} \right) \quad (5)$$

where  $\alpha_{f,i}(t)$  and  $\beta_{f,i}$  are specific to each fault, with  $L_{f,i}$  and  $d_{f,i}(t)$  representing the length and distance affected by each fault.

The reliability and precision of telesurgery systems can be significantly enhanced by understanding and addressing these delays and faults in the optical fibers for ensuring effective and accurate operations.

#### B. Fault Detection Layer

The dataset [11] has 125,832 rows and 36 columns filled with processed sequences from OTDR traces. These traces show us different fiber faults like cuts in the fiber, tapping issues, bad connections, bends in the fiber, dirty connectors, and more. Each OTDR trace sequence has key features like signal-to-noise ratio (SNR), a normalized sequence of 30 lengths, what type of fiber event it is, where it happens, and normalized values for reflectance and loss. Once it has been

preprocessed, this dataset is used for training and prediction tasks.

We selected three DL models to evaluate their effectiveness in detecting faults: Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU), and Long Short-Term Memory (LSTM). During training, we utilized three different optimizers: Adam, Nadam, and RMSprop. The primary goal of this training was to fine-tune these models so they could accurately identify faults in optical fibers based on processed OTDR trace sequences. Of all the models tested, LSTM emerged as the most proficient at detecting faults in optical cables. The data preprocessing steps and model training process are shown in Algorithm 1.

The training of LSTM using the RMSprop optimizer and categorical cross-entropy loss is described by:

$$\phi_{t+1} = \phi_t - \frac{\alpha}{\sqrt{v_t} + \delta} \odot \nabla_{\phi_t} C(\phi_t) \quad (6)$$

where:

$$v_t = \beta \cdot v_{t-1} + (1 - \beta) \cdot (\nabla_{\phi_t} C(\phi_t))^2 \quad (7)$$

The RMSprop optimizer plays a vital role in updating the LSTM parameters denoted by  $\phi$ . It has a learning rate referred to as  $\alpha$  and a decay rate  $\beta$  to control the moving average of squared gradients. To avoid division by zero errors we add a small constant  $\delta$ . The gradient  $\nabla_{\phi_t} C(\phi_t)$  means the gradient of the categorical cross-entropy loss function with respect to parameters  $\phi_t$ . This method has the advantage of regularizing updates by controlling the rate at which recent gradient magnitudes are learned.

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**Algorithm 1** Data Preparation and Model Training

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- 1: **Input:** Dataset  $\mathcal{D} = \{(\mathbf{x}_k, z_k)\}_{k=1}^K$
- 2: **Optimizers:**  $\mathcal{O} = \{O_1, O_2, O_3\}$
- 3: **Output:** Trained Models  $\mathcal{M} = \{M_{\text{RNN}}, M_{\text{GRU}}, M_{\text{LSTM}}\}$
- 4: Extract features:  $\mathbf{X} = \{\mathbf{x}_k\}_{k=1}^K$
- 5: Labels:  $\mathbf{z} = \{z_k\}_{k=1}^K$
- 6: Encode labels:  $\mathbf{Z} = \text{to\_categorical}(\text{LabelEncoder}(\mathbf{z}))$
- 7: Impute missing values:

$$X_{kl} = \begin{cases} \text{mode}(X_{.l}) & \text{if } X_{kl} \text{ is categorical} \\ \text{median}(X_{.l}) & \text{if } X_{kl} \text{ is numerical} \end{cases}$$

- 8: Split data:

$$(\mathbf{X}, \mathbf{Z}) \rightarrow (\mathbf{X}_{\text{train}}, \mathbf{X}_{\text{test}}), (\mathbf{Z}_{\text{train}}, \mathbf{Z}_{\text{test}})$$

- 9: Reshape data:

$$\mathbf{X}_{\text{train}}, \mathbf{X}_{\text{test}} \rightarrow \mathbf{X}^{(n,t,f)}$$

- 10: **for** each  $O_i \in \mathcal{O}$  **do**
  - 11:   **for** each  $M_j \in \mathcal{M}$  **do**
  - 12:     Train  $M_j$  with  $O_i$  on  $(\mathbf{X}^{(n,t,f)}, \mathbf{Z}_{\text{train}})$
  - 13:     Evaluate  $M_j$  on  $(\mathbf{X}^{(n,t,f)}, \mathbf{Z}_{\text{test}})$
  - 14:   **end for**
  - 15: **end for**
  - 16: **Output:** Metrics( $M_j, O_i$ )
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### C. Patient Layer

In this layer, the aim is to make the telesurgery system adjust to specific patient data and safety needs in real time. Here, we mix in patient parameters, called  $\mathbf{P}(t)$ , with feedback signals, known as  $\mathbf{F}(t)$ . This lets the robotic system change its actions based on what each patient requires. To keep things safe during surgery, we use a safety check called a constraint function  $\phi(\mathbf{P}(t))$ . This must follow this rule:

$$\phi(\mathbf{P}(t)) \leq \epsilon \quad (8)$$

where  $\phi(\mathbf{P}(t))$  shows patient-specific safety measures, and  $\epsilon$  is the safety limit we have set. It makes sure the system stays within safe levels that fit the patient's condition. Also, this Patient Layer works together with the Fault Detection Layer. They keep an eye on delays caused by issues like optical fiber faults, marked as  $\Delta T_{\text{fault}}$ . When faults are found, they help make real-time changes to ensure the communication stays reliable and effective during surgery. The adaptability of the Patient Layer is essential for achieving both precision and safety in telesurgical operations by continuously refining system responses based on patient data and detected faults.

## IV. RESULT ANALYSIS

This section shows the proposed framework's performance analysis using various evaluation metrics parameters, such as training accuracy, loss, precision, recall, and F1 score.

### A. Experimental Setup and Tools

This experimental setup of the paper uses high-end processors with a server having an x86-64 architecture, two T4 GPUs, 12 GB of RAM, and 108 GB of hard disk space. PyTorch ML framework and the NumPy were used which helps in the encapsulation of numerical functions and helps in faster calculations of data, and used various libraries like GitPython-3.1.42, datasets-2.18.0, dill-0.3.8, docker-py creds-0.4.0, gitdb-4.0.11, multiprocessing-0.70.16.

### B. Accuracy Comparison

The accuracy of the RNN, GRU, and LSTM models is shown in Fig. 2a, 2b, and 2c. Each model used different optimizers: Adam, Nadam, and RMSprop out of which LSTM stands out and perform well with all the optimizers. Its accuracy is 0.8018 with Adam, 0.8193 using Nadam, and a high of 0.8328 with RMSprop. The GRU model performs the best with Adam at 0.7705, next is Nadam at 0.7194, followed by RMSprop at 0.6668. As for the RNN model it hits its top score of 0.7567 with RMSprop. With Nadam, it gets 0.7127 and 0.7072 with Adam. These findings show how different optimizers affect how well each model works.

### C. Accuracy and Loss Comparison of LSTM

The LSTM model's accuracy and loss metrics were tracked across epochs using three optimizers: Adam, Nadam, and RMSprop. You can see these in Fig. 3. Looking at the accuracy chart in Fig. 3a, it shows that RMSprop achieved the best final accuracy at 0.8328. Nadam follows with an

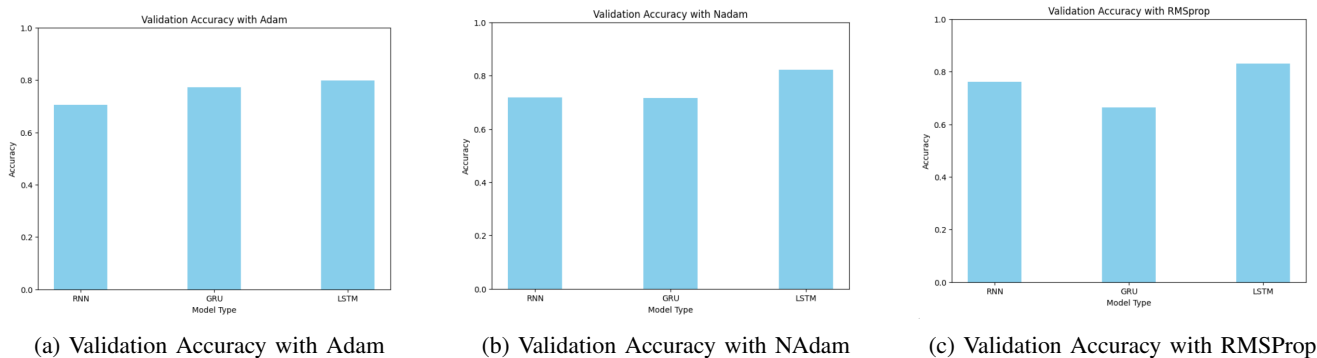


Fig. 2: Comparison of Accuracy Metrics with Adam, NAdam and RMSProp Optimisers

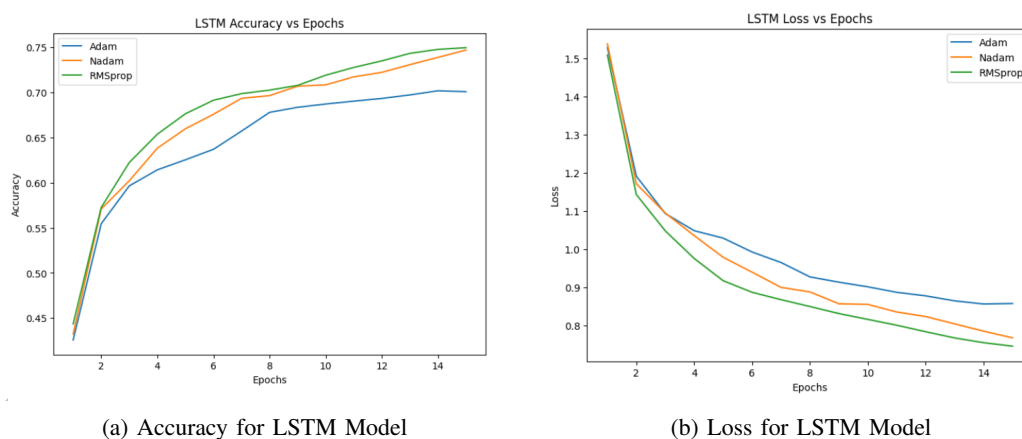


Fig. 3: Accuracy and Loss Graphs for LSTM Model

accuracy of 0.8193, while Adam ends up at 0.8018. Now, if we check the loss in Fig. 3b, we see a similar trend. RMSprop gives us the lowest final loss of 0.5315. That's better than Nadam, which is at 0.5557, and then comes the Adam in last at 0.6081.

#### D. Precision, Recall and F1 score Comparison of LSTM

Fig. 4 shows how well the LSTM model did with the Adam, Nadam, and RMSprop optimizers across 15 epochs. When we look at precision, in Fig. 4a, it's clear that RMSprop does the best. It hits a final validation precision of 0.8514. Nadam comes next with 0.8364. Adam starts well but ends lower at 0.8078. This means RMSprop is better at reducing false positives and gives more accurate positive predictions when we compare it to Nadam and Adam. Turning to recall trends in Fig. 4b, RMSprop ranked first again with a final recall of 0.8328, showing it's good at finding true positives. Nadam's recall is 0.8193, while Adam stands at 0.8018. These numbers are a bit lower, but they stay steady. So, RMSprop seems really good at cutting down missed classifications in the dataset, while Nadam stays close behind. Now let's discuss the F1 score in Fig. 4c. This score shows how well both precision and recall work together. RMSprop scores highest here too, with a final F1 score of 0.8320. Next is Nadam at 0.8192 and then Adam at 0.7985. The trends in F1 scores show that RMSprop not only boosts

precision and recall on their own but also gives the best overall mix of both things, making it the top pick for this kind of classification task. Nadam performs solidly across all measures. It can be a great backup choice, especially for balancing recall and precision. Adam trails just a bit but still shows decent strength overall, it may work for tasks that don't need super fine-tuned optimization for both metrics. These results shows that RMSprop is the best optimizer and performs well for tasks that need a balance between true and false positives. Nadam keeps up by having good recall rates too while Adam brings stability across all measures—even though it's not quite as strong as the others.

#### E. ROC Curve Comparison

In this study, we used Receiver Operating Characteristic (ROC) curves. They are shown in Fig. 5. These curves help us see how well the RNN, GRU, and LSTM models using Adam, NAdam, and RMSprop optimizers. All the models performed well at classifying task and their AUC values were close to 1. As seen in Fig. 5a, the RNN got the highest AUC with RMSprop, hitting 0.9657. The GRU with Adam shown in Fig. 5b followed closely at 0.9710. Finally, the LSTM model using RMSprop reached 0.9800 as shown in Fig. 5c. Out of all these, the LSTM model with RMSprop stood out as the best performer. It showed the best overall performance and made very few false positives.

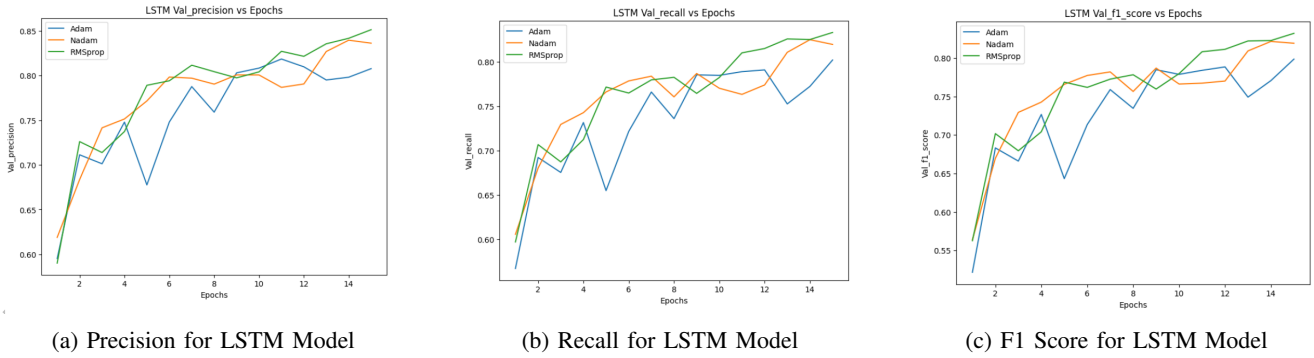


Fig. 4: Precision, Recall, and F1 score graphs for LSTM model.

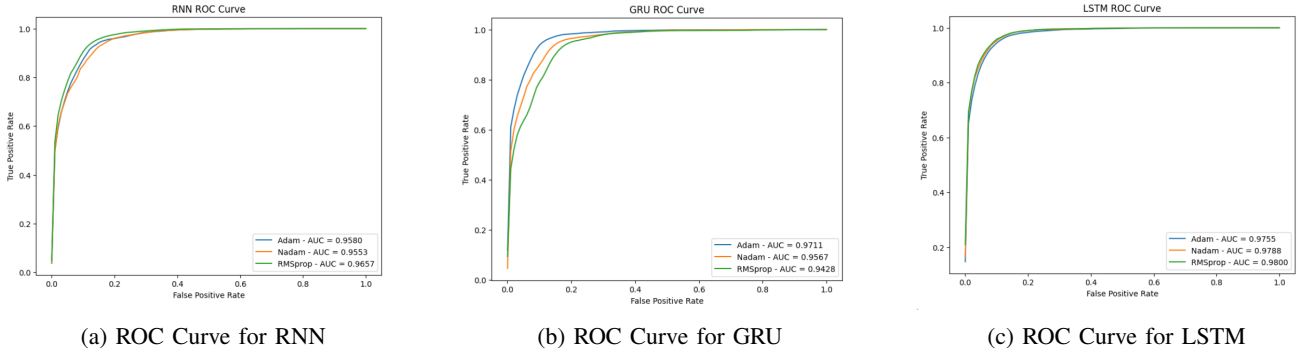


Fig. 5: ROC curves for different DL models.

## V. CONCLUSION

In conclusion, this study focuses on the significance of AI-based fault detection in optical fibre communication systems for telesurgery. By utilizing DL models such as RNN, GRU and LSTM along with optimisers like Adam, Nadam and RMSprop, we have achieved notable improvement in the accuracy of fault detection and reliability. Particularly to focus upon the LSTM model, it exhibited superior performance with RMSprop, recoding the highest accuracy and the lowest loss among all the other tested models. This enhancement is important for improving the fault detection accuracy and maintaining the low latency requirements. The proposed framework not only focuses on reliability but also focuses on the real time fault management therefore mitigating the potential delays and thus ensuring the precision of remote surgeries. Future work will be targeting on distending the datasets, embracing additional fault scenarios and also emphasizing on surveying over more innovative AI techniques to enhance the adaptivity and robustness of the system.

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