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# Decoding Intracranial Pressure Wave: A Deep Learning Approach

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**ABSTRACT:** Monitoring neurological well-being is critical for timely identification and management of various neurological disorders. Recent advancements in medical technology have paved the way for exploring innovative methods in non-invasive monitoring techniques. In our study, we propose utilizing intercranial pulse waveform analysis as a novel approach to enhance neurological health monitoring. Pulse waveforms within the cranial cavity contain vital data on intracranial pressure dynamics, cerebral blood flow, and cerebrovascular compliance. By examining attributes like waveform morphology, amplitude, and frequency, our aim is to extract insights into the underlying neurological health status. Our research aims to develop robust algorithms for capturing, processing, and analysing intercranial pulse waveforms. We will utilize advanced signal processing techniques, such as wavelet transform and spectral analysis, to extract relevant features from the pulse waveforms. Additionally, machine learning algorithms will be employed to establish correlations between these features and established neurological parameters and clinical outcomes. The proposed methodology will be validated using data from a cohort of patients undergoing neurological monitoring for various conditions, including traumatic brain injury, stroke, and intracranial hypertension. We anticipate that our approach will facilitate the early detection of neurological abnormalities, enabling personalized treatment strategies and improving patient outcomes. In conclusion, intercranial pulse waveform analysis shows significant promise as a non-invasive, real-time monitoring technique for advanced assessment of neurological health. By adopting this approach, clinicians can gain valuable insights into intracranial dynamics, ultimately leading to improved management of neurological conditions and higher standards of patient care. **Keywords:** neurological health monitoring, intercranial pulse waveform, spectral analysis, machine learning.

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## I. INTRODUCTION

- The field of neurology is constantly evolving, driven by the pursuit of improved diagnostic and monitoring techniques to enhance patient care and outcomes. Central to this Endeavor is the development of advanced methods for monitoring neurological health, especially those offering non-invasive, immediate insights into intracranial dynamics. In recent years, there has been a shift away from traditional diagnostic approaches towards innovative methods leveraging the inherent physiological signals within the human body.
- One promising avenue of exploration is the analysis of intercranial pulse waveforms for neurological health monitoring. These waveforms, originating from the pulsatile blood flow within the cranial vasculature, contain valuable information about intracranial pressure dynamics, cerebral blood flow characteristics, and cerebrovascular compliance. By carefully analysing the intricate patterns and characteristics of these pulse waveforms, a pathway emerges to decipher the underlying neurological health status of individuals.
- This approach offers several advantages over conventional monitoring methods. Firstly, it is non-invasive, eliminating the need for invasive procedures such as intracranial catheterization, thereby reducing the risk of complications and increasing patient comfort during monitoring. Secondly, intercranial pulse waveform analysis provides real-time data, enabling clinicians to quickly identify **changes in intracranial dynamics and intervene as necessary. This is particularly important in critical care settings where timely intervention can have a significant impact on patient outcomes.**

- Furthermore, intercranial pulse waveform analysis has the potential to provide comprehensive insights into various aspects of neurological health. Beyond simply assessing intracranial pressure, it can reveal information about cerebral perfusion, vascular compliance, and neurovascular coupling. This holistic understanding of neurological health can guide treatment decisions, facilitating tailored interventions tailored to individual patient needs.
- In summary, the exploration of intercranial pulse waveforms represents a fertile frontier in neurological health monitoring. By leveraging the physiological signals within the cranial vasculature, this approach offers non-invasive, real-time insights into intracranial dynamics, thereby contributing to improved patient care and outcomes in the field of neurology.

## II. RELATED WORK

- Literature Examination: Undertake an exhaustive examination of existing literature concerning neurological health surveillance, encompassing investigations into prevailing diagnostic methodologies, monitoring approaches, and their constraints. This scrutiny should encompass both scholarly research articles and industry analyses.
- Current Technological Landscape: Delve into the realm of existing technologies and apparatus utilized for neurological surveillance, ranging from imaging techniques (e.g., MRI, CT scans) to invasive procedures (e.g., intracranial pressure monitoring) and non-invasive modalities (e.g., EEG, fMRI). Evaluate their efficacy, limitations, and suitability for continuous monitoring.
- Signal Analysis Methods: Explore methodologies for signal analysis employed in neurological surveillance, encompassing techniques for interpreting pulse waveforms, EEG signals, and other physiological data. Assess the feasibility of these methods for real-time analysis and detection of neurological anomalies.
- Utilization of Machine Learning in Healthcare: Investigate the integration of machine learning algorithms in healthcare, with a specific focus on neurological surveillance. Scrutinize the potential applications of these algorithms in deciphering intricate physiological data and identifying patterns indicative of neurological disorders.
- Non-Invasive Monitoring Solutions: Scrutinize ongoing research and advancements in non-invasive monitoring solutions for neurological well-being, such as wearable devices, remote monitoring systems, and innovative sensor technologies. Evaluate their capacity to deliver continuous, real-time surveillance while circumventing the limitations of existing methodologies.
- Clinical Trials and Research: Review clinical trials and research endeavors centered on neurological surveillance techniques and their impact on patient outcomes. Identify effective approaches and areas necessitating refinement in terms of sensitivity, specificity, and usability.
- Regulatory Framework: Explore the regulatory directives and prerequisites governing medical devices and surveillance systems, particularly within the domain of neurological health. Grasp the regulatory hurdles and considerations intrinsic to the development and deployment of novel surveillance solutions.
- Industry Dynamics and Innovations: Investigate prevailing industry trends and innovative strides in neurological surveillance, including collaborative ventures between healthcare entities, technology firms, and research establishments. Identify emerging technologies and potential collaborative ventures aimed at advancing non-invasive surveillance solutions.
- By meticulously scrutinizing related works in these domains, researchers can glean invaluable insights into the current landscape of neurological health surveillance, thereby pinpointing avenues for innovation and enhancement.

## III. PROBLEM DEFINITION

- The dilemma surrounding neurological health monitoring arises from the shortcomings of current diagnostic techniques and the necessity for continuous, non-invasive surveillance methods. Present methodologies, such as imaging and invasive procedures, yield valuable insights but are hindered by their invasive nature, intermittent application, and absence of immediate data. These limitations impede the prompt identification and management of neurological issues, impacting both patient outcomes and healthcare resources.
- Furthermore, neurological conditions exhibit diverse manifestations and necessitate a comprehensive monitoring strategy. Existing diagnostic approaches often lack the precision to detect subtle changes, particularly in conditions characterized by dynamic intracranial dynamics like brain injury, stroke, and elevated cranial pressure.
- Hence, the crux of the matter lies in the pressing need for a non-invasive monitoring solution that transcends the constraints of current methodologies, furnishing timely insights into neurological well-being. Such a solution should enable continuous monitoring to detect subtle alterations indicative of neurological issues and should be



adaptable to various conditions. Additionally, it should possess the sensitivity to recognize early signs of deterioration, facilitating timely intervention and tailored treatment.

- Addressing this challenge entails the development of a novel monitoring paradigm that leverages physiological signals from the cranial vasculature to deliver real-time insights into neurological health. This encompasses the analysis of intercranial pulse waveforms and the establishment of robust methodologies for data acquisition, processing, and interpretation. By surmounting these hurdles, our aim is to revolutionize neurological health monitoring, leading to earlier detection, personalized interventions, and enhanced outcomes for individuals with neurological disorders.

## IV. METHODOLOGY

### 4.1 System Implementation Overview

The implementation phase of the system for intercranial pulse waveform analysis entails translating design specifications into operational software and hardware components. Below is an overview of the process:

- **Software Development:**
  - **Frontend Development:** Crafting and executing the user interface (UI) featuring interactive dashboards, visualization tools, and user controls.
  - **Backend Development:** Establishing the backend infrastructure to facilitate data acquisition, signal processing, analysis, and integration.
- **Hardware Integration:**
  - **Sensor Integration:** Embedding non-invasive sensors such as PPG sensors and accelerometers into the system hardware.
  - **Data Acquisition Unit:** Creating or configuring the unit to capture, preprocess, and digitize pulse waveform signals from the sensors.
- **Signal Processing and Analysis:**
  - **Algorithm Implementation:** Deploying signal processing algorithms like wavelet transform, Fourier analysis, and machine learning models for pulse waveform interpretation.
  - **Real-time Processing:** Enhancing algorithms for swift processing to ensure timely analysis and responsiveness.
- 1. **Data Integration and Fusion:**
  - Data Integration: Developing modules to merge data from various sources including clinical assessments, medical imaging, and physiological monitoring devices.
  - Integration Testing: Conducting tests to verify the interoperability and functionality of data integration and fusion modules.
- 2. **User Acceptance Testing (UAT):**
  - Test Planning: Devising plans and scenarios to assess the system's functionality, usability, and performance against user requirements and acceptance criteria.
  - UAT Execution: Testing with clinicians and stakeholders to validate system functionality, usability, and alignment with user expectations.
- 3. **Deployment and Rollout:**
  - Deployment Planning: Strategizing hardware installation, software configuration, and data migration procedures.
  - Deployment Execution: Implementing the system in clinical settings according to the devised plan.
- 4. **Training and Support:**
  - **User Training:** Providing training sessions for clinicians and end-users to familiarize them with the system's features, functionality, and usage guidelines.
  - **Technical Support:** Establishing protocols for offering assistance, troubleshooting, and ongoing maintenance services to address user inquiries and system issues.

**5. Documentation and Knowledge Transfer:**

- **Documentation:** Creating comprehensive documentation including manuals, system architecture diagrams, API documentation, and troubleshooting guides.
- **Knowledge Transfer:** Sharing expertise with internal teams or external support partners responsible for maintaining and supporting the system post-deployment.

**6. Monitoring and Optimization:**

- **Performance Monitoring:** Implementing tools and metrics to continuously assess performance including data acquisition rates, processing times, and resource utilization.
- **Optimization:** Identifying opportunities for improvement based on feedback and implementing enhancements, updates, and patches to optimize system performance.

**7. Regulatory Compliance and Validation:**

- **Compliance Validation:** Conducting checks and validations to ensure adherence to relevant standards, regulations, and guidelines.
- **Validation Testing:** Performing tests to demonstrate safety, efficacy, and compliance with regulatory requirements.

**4.2 Proposed Model**

In our envisioned model for analyzing intercranial pulse waveforms, we aim to revolutionize neurological health monitoring. This innovative system offers clinicians a non-invasive, instantaneous monitoring solution, providing crucial insights into intracranial activities. By integrating cutting-edge technology with advanced signal processing methods, we dissect pulse waveform signals obtained from the scalp's surface, enabling early detection of neurological issues and personalized treatment. Below is a summary of our proposed system.

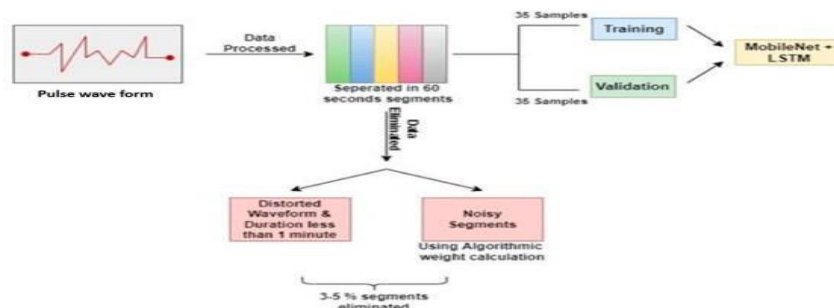


Fig 4.1 System architecture

**Pulse Waveform Acquisition:** The system employs comfortable, wearable sensors such as PPG sensors or accelerometers, positioned on the head to capture pulse waveform signals. These sensors ensure the real-time capture of high-fidelity pulse waveform signals.

**Signal Processing and Examination:** Cutting-edge techniques like wavelet transform, Fourier analysis, and machine learning algorithms process and analyze the captured pulse waveform signals. Essential parameters such as waveform morphology, amplitude, frequency, and timing are extracted.

**Interactive Interface:** An intuitive interface enables clinicians to interact with real-time data effectively. Clinicians can visualize pulse waveform signals, monitor alterations in neurological health, and utilize diagnostic algorithms for automated detection of anomalies.

**Holistic Data Integration:** Data from various sources including clinical assessments and medical imaging are seamlessly integrated into the system for a comprehensive evaluation of neurological health. Fusion algorithms amalgamate data from multiple sources to bolster accuracy and reliability.

**Validation and Deployment:** Stringent validation studies evaluate accuracy, sensitivity, and specificity. Clinical validation in diverse settings assesses performance and impact on patient outcomes.

**Data Security and Confidentiality:** Robust security measures ensure the confidentiality and integrity of patient data. Compliance with regulations such as HIPAA guarantees patient privacy protection.

**Scalability and Integration:** The system is scalable and adaptable to various healthcare environments, seamlessly integrating with existing electronic health record systems and medical devices.

The proposed system represents a significant leap forward in neurological health monitoring, equipping clinicians with tools for early detection and personalized management. Its innovative features contribute to enhancing patient care and propelling the field of neurological health monitoring forward.

### 4.3 LSTM ALGORITHM

Long Short-Term Memory (LSTM) architecture embodies a specialized form of recurrent neural network (RNN) design crafted to manage sequential data efficiently. This renders it particularly adept at tasks like forecasting time series, comprehending language nuances, and identifying speech patterns. LSTM networks are meticulously engineered to address inherent challenges encountered in conventional RNNs, notably the vanishing gradient dilemma. This obstacle hampers the RNN's ability to adeptly grasp and retain information over prolonged sequences.

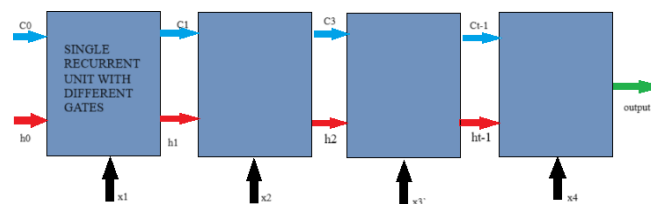


Fig 4.2 LSTM Architecture

The core elements of an LSTM unit encompass:

- **Memory Cell:** Serving as a "memory bank," the cell state stores information throughout various time steps, enabling the network to selectively retain or discard details pertinent to the current task.
- **Forget Gate:** Responsible for determining which information stored in the cell state should be discarded or "forgotten," based on input and past hidden states. It utilizes a sigmoid activation function to assign importance scores to elements within the cell state.
- **Input Gate:** Decides which new information should be incorporated into the cell state. Consisting of a sigmoid layer for deciding which values are updated and a tanh layer for proposing candidate values, this gate assists in adjusting the cell state accordingly.
- **Output Gate:** Regulates the selection of relevant information from the updated cell state to generate the output for the current time step. By employing a sigmoid activation function, it filters the cell state to produce the final output of the LSTM unit.

Training LSTM networks entails employing backpropagation through time (BPTT), an extension of the standard backpropagation algorithm for RNNs. Throughout training, the network adapts its parameters (weights and biases) to minimize a specified loss function, such as mean squared error or cross-entropy loss, by updating gradients based on the error.

In the domain of time series prediction, LSTM networks are trained to anticipate future values of a time series based on historical data. By consuming a sequence of past observations as input, the network learns to generate forecasts for future time steps. Leveraging the memory capabilities inherent in LSTM units, the network can capture intricate long-term patterns and dependencies within the time series data, making it an invaluable tool for predictive tasks.

In essence, LSTM networks excel at modeling sequential data and have demonstrated successful implementations across diverse fields, including finance, healthcare, and natural language processing. Their capacity to comprehend long-term dependencies and preserve information over extended sequences makes them exceptionally proficient at handling tasks involving sequential data and dynamic decision-making processes.

#### 4.4 DATA COLLECTION

**Specialized Care Unit for Normotensive Patients (SCUN):** This unit, situated within a hospital, specializes in providing comprehensive care for individuals with severe neurological disorders. It offers continuous monitoring and treatment round-the-clock for patients afflicted with conditions like traumatic brain injury, stroke, or aneurysmal subarachnoid hemorrhage (ASAH).

**Retrospective Examination:** This denotes the scrutiny and analysis of data obtained from past occurrences or records. In this instance, researchers examined data sourced from 50 patients admitted to the SCUN over a span of five years (2014-2019) to investigate specific aspects of their medical histories and treatment outcomes.

**Assessment of Intracranial Pressure (ICP) Recordings:** Patient selection for analysis was based on the availability and satisfactory quality of intracranial pressure (ICP) recordings, a pivotal parameter in neurological condition monitoring. This criterion ensures the reliability and suitability of the data used in the study.

**Ethical Approval from the Ethics Committee:** Prior to commencing the study, approval was sought from the Ethics Committee at the Wroclaw Medical University, Poland. This ensures compliance with ethical standards and guidelines pertaining to the treatment of human subjects and the utilization of their medical data.

**Traumatic Brain Injury (TBI):** TBI refers to brain damage resulting from an external force, such as a blow or impact to the head. In this study, 39 out of the 50 patients had experienced TBI, making it the primary focus of the investigation.

**Aneurysmal Subarachnoid Hemorrhage (ASAH):** ASAH is a type of stroke caused by bleeding into the space surrounding the brain due to an aneurysm rupture. Eleven patients included in the study had ASAH, serving as a secondary focus for comparison and analysis.

**Intracranial Volume Equilibrium:** This concept pertains to the balance between brain tissue, blood, and cerebrospinal fluid volumes inside the skull. Disruptions in this equilibrium, as seen in TBI or ASAH cases, can lead to alterations in intracranial pressure and impact neurological function.

**Glasgow Coma Scale (GCS):** The GCS is a neurological assessment tool used to gauge the level of consciousness and neurological function in patients with brain injuries. It evaluates eye opening, motor response, and verbal response, with lower scores indicating more severe impairment.

**Glasgow Outcome Scale (GOS):** The GOS assesses overall outcome and disability following a brain injury, measuring functional independence and cognitive ability. Scores range from I (indicating death) to V (indicating good recovery).

**Adherence to Treatment Protocols:** Patients with TBI and ASAH were managed in accordance with established guidelines from reputable organizations such as the American Brain Trauma Foundation and the American Heart Association/American Stroke Association. These guidelines offer evidence-based recommendations for optimizing the management of these conditions and enhancing patient outcomes.

#### 4.5 DATA PREDICTION

In this study, various models underwent examination; however, this manuscript focuses on the most efficient ones: the 1-D Residual Neural Network (ResNet) and its variations—a dual-channel network combining ICP and ABP signals or Siamese feature extractors—and the Long-Short Term Memory Fully Convolutional Network (LSTM-FCN). The fully connected neural network acted as the reference for our discoveries. Additionally, the methodology detailed in a previous publication was adapted for multi-class prediction to compare against the proposed models, utilizing the same training techniques.

Convolutional neural networks (CNNs) extrapolate insights not solely from individual data points but also from their surrounding contexts, making them ideal for morphological prediction tasks. Furthermore, given the short duration of processed signals (typically less than 1 second), these networks circumvent the challenges associated with modeling long-term dependencies. ResNets, complex convolutional models integrating residual connections between layers, enable more resilient error propagation. Hyperparameters were meticulously chosen through empirical approaches across numerous experiments with each model variation. The structure of the residual models is illustrated in Figure 4, and detailed hyperparameters are provided in Appendix I.

Moreover, an alternative approach involved modifying the number of channels in the initial layer of the network and exploring a Siamese architecture with residual feature extractors. However, unlike the original study, the latter was trained using conventional procedures rather than a contrastive loss function. This strategy aimed to emulate the decision-making process of manual annotators, who consider features from both ICP and ABP signals.

#### 4.6 DATA MODULE AND EVALUATION

Multiple models were scrutinized in this study, with a focus on the most effective ones: the 1-D Residual Neural Network (ResNet) and its variations—a dual-channel network amalgamating ICP and ABP signals or Siamese feature extractors—and the Long-Short Term Memory Fully Convolutional Network (LSTM-FCN). A fully connected neural network served as the benchmark for our analysis. Additionally, the methodology outlined in a previous publication was adjusted for multi-class classification to compare against the proposed models, utilizing consistent training methods.

Convolutional neural networks (CNNs) extract insights not only from individual data points but also from their surrounding context, making them suitable for morphological classification tasks. Moreover, given the short duration of processed signals (mostly less than 1 second), these networks do not face challenges in modeling long-term dependencies. ResNets, complex convolutional models incorporating residual connections between layers, facilitate more robust error propagation. Hyperparameters were meticulously chosen through empirical methods across numerous experiments with each model variant. The architecture of the residual models is illustrated in Figure 4, with detailed hyperparameters provided in Appendix I.

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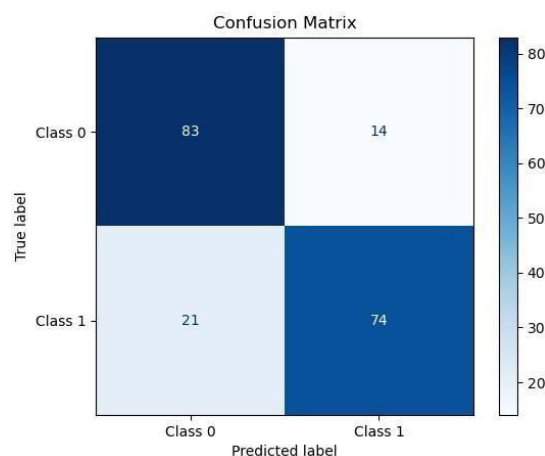


Fig 4.3 Confusion Matrix



Moreover, a different approach was adopted, which entailed adjusting the quantity of channels in the network's initial layer and investigating a Siamese architecture incorporating residual feature extractors. However, unlike the initial study, the latter was trained utilizing conventional methods rather than a contrastive loss function. This methodology aimed to emulate the decision-making process of manual annotators, who evaluate characteristics from both ICP and ABP signals.

## V. RESULT

### 5.1 CLASSIFICATION RESULTS

The data depicted in Table III provides a comprehensive overview of the classification accuracy achieved by the top-performing models compared to the baseline accuracy of the fully connected network. This comparative analysis illuminates the relative efficacy of each model in accurately classifying data points. The results presented in the table encapsulate the culmination of a rigorous process involving meticulous fine-tuning of hyperparameters through iterative experimentation. Each variant of the model reached its optimal performance, showcasing its utmost potential in identifying patterns within the data.

Remarkably, all iterations of the ResNet model, as well as the LSTM-FCN model, demonstrated superior performance compared to the fully connected network. This superiority underscores the effectiveness of employing sophisticated neural network architectures to address intricate classification tasks. Particularly noteworthy is the exceptional performance of the single-channel ResNet variant, which solely utilized the ICP signal as input. This discovery highlights the effectiveness of utilizing specific data streams independently to achieve optimal classification accuracy. Interestingly, contrary to expectations, the inclusion of the ABP signal in the dual-channel and Siamese ResNet configurations did not result in a significant improvement in classification accuracy across the validation and test datasets. However, it is worth noting that the dual-channel ResNet model exhibited commendable accuracy in the training dataset, suggesting potential areas for further exploration or refinement.

A detailed examination of the nuances of these findings can be found in Appendix II, offering valuable insights into the factors influencing model performance. Notably, even when subjected to additional complexities such as the integration of artificially generated A+E examples, gradient weighting, or unsupervised pretraining, the single-channel ResNet model maintained its superiority in accuracy. Furthermore, it is essential to underscore the comparative performance of the modified model proposed in a previous study. While demonstrating comparable accuracy in the training dataset, this model notably lagged behind when compared to the ResNet variants in the other two datasets, emphasizing the importance of continuous refinement and evolution in model architecture and training methodologies.

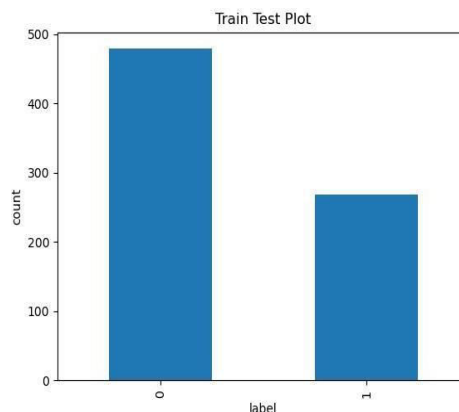


Fig 5.1: Trained Graph

### 5.2 PREDICT RESULTS

The advancement of intracranial pressure (ICP) waveform analysis has emerged as a focal point in research on normotensive care, representing a significant departure from conventional methods. In the pursuit of heightened diagnostic accuracy and predictive capabilities, researchers have embarked on a quest to unravel the intricate patterns

embedded within ICP waveforms. This endeavor necessitates a shift away from traditional approaches, advocating for the adoption of innovative paradigms rooted in advanced computational techniques and machine learning algorithms.

At the heart of this evolution lies the transition from basic ICP monitoring to sophisticated waveform analysis. Through the utilization of convolutional neural networks (CNNs) and long-short term memory fully convolutional networks (LSTM-FCNs), researchers aim to extract subtle morphological features inherent within ICP waveforms. This shift underscores a profound acknowledgment of the inherent complexity and richness of ICP signals, moving beyond simplistic interpretations to explore the intricacies of waveform morphology.

As researchers venture into this unexplored domain, they encounter numerous challenges and opportunities. The integration of dual-channel networks, encompassing both ICP and arterial blood pressure (ABP) signals, signifies a departure from unimodal analyses toward a comprehensive understanding of neurophysiological dynamics. Despite initial optimism surrounding the incorporation of ABP signals, the observed lack of significant enhancements in classification accuracy highlights the need for further investigation and refinement.

Furthermore, the introduction of Siamese feature extractors adds a new dimension to waveform analysis, mirroring the decision-making processes employed by manual annotators. While this innovative approach holds promise in theory, rigorous validation and optimization are essential to realize its full potential.

In essence, the evolution of intercranial pressure waveform analysis symbolizes a paradigm shift in normotensive care, ushering in a new era of precision medicine and tailored patient management. By embracing cutting-edge computational methodologies and leveraging the complexity of ICP waveforms, researchers are poised to unlock unprecedented insights into neurological pathophysiology and transform clinical decision-making paradigms.

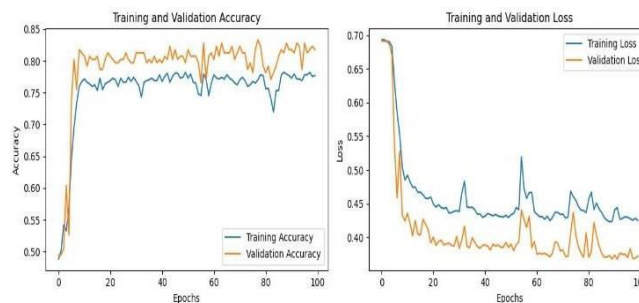


Fig 5.2 Training and Testing Accuracy

## VI. CONCLUSION

In this research, we investigated the potential of deep neural networks to identify various shapes of intercranial pressure (ICP) pulse waveforms and to detect artifacts within recordings from patients with intracranial pathologies. Due to the limited prior research on morphological classification of ICP pulse waveforms using deep learning methods, we conducted a thorough exploration employing diverse models, data representations, and training and evaluation techniques.

Our results revealed that the single-channel ResNet model, which utilized a 1-D vector of ICP signal samples as input, emerged as the top performer, achieving an impressive classification accuracy of 86% (82% strict accuracy) in an independent test dataset. This suggests the potential of the model to accurately classify ICP pulse waveform shapes with high precision. Notably, our proposed approach demonstrated resilience to variations in recording length, as waveform classification operated on a single-pulse level, independent of pulse positioning within the entire recording.

The complexity of the task was evident from the observation that neither different models nor alternative data representations led to further improvements in accuracy. This complexity stems from the continuous nature of changes in brain compliance reflected in waveform shape alterations, leading to ambiguous waveform features. Despite this

challenge, our models demonstrated the ability to correctly classify a large percentage of pulses from a completely different data distribution, indicating acceptable performance.

Interestingly, incorporating the arterial blood pressure (ABP) signal alongside the ICP signal did not enhance model performance. The single-channel ResNet model outperformed its dual-channel and Siamese counterparts, with the additional ABP signal increasing the models' susceptibility to overfitting. However, this simplicity enables lower computation time, theoretically enabling continuous and real-time classification.

Our proposed end-to-end pipeline, which includes single pulse detection and artifact exclusion alongside waveform classification, shows promise for real-time processing. By treating artifact detection as part of the classification stage, we streamline the analysis process, addressing clinically insignificant signal disturbances. This approach contrasts with traditional methods that employ separate algorithms for artifact detection, providing a more integrated and efficient solution. Interestingly, the manual classification of ICP pulses traditionally involved analysis of both the ICP and corresponding arterial blood pressure (ABP) signals. This approach was informed by prior studies highlighting the correlation between the systolic portion of ABP and the P1 segment of the ICP pulse waveform. Surprisingly, incorporating the ABP signal did not enhance the performance of deep learning models, with the single-channel ResNet model surpassing both its dual-channel and Siamese counterparts, while the addition of the ABP signal introduced complexities leading to overfitting.

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