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###### **КУРСОВАЯ РАБОТА**

Классификация медицинских изображений с использованием жидкой нейронной сети в клиническом применении

Medical Image Classification using Liquid Neural Network in Clinical Application

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# Abstract

    This term paper investigates how useful Liquid Time-Constant neural networks are to classify medical images. It compares LTC networks and to the traditional recurrent and small convolutional networks using publicly available MedMNIST datasets. LTC models did not always offer significant advantages over small convolutional networks while having similar number of parameters. However, they outperform their RNN and LSTM counterparts in most configurations, while being significantly smaller. The study suggests that Liquid layers is a competitive choice of a neural network architecture, especially when time-series nature of data is important, however further research is needed on more complex datasets.

**Keywords:** liquid neural networks, MedMNIST datasets, recurrent neural networks, medical images analysis, time-series data

**Source code:** <https://github.com/As17-01/LungTissues/tree/main/scripts/MNIST>

# Абстракт

    В этой курсовой работе исследуется насколько полезные Жидкие нейронные сети для классификации медицинских изображений. Она сравнивает LTC сети с традиционными рекуррентными и небольшими сверточными сетями, используя публично доступные базы данных MedMNIST. LTC модели не всегда показывали значительного преимущества над компактными сверточными сетями, имея схожее количество параметров. Однако они превосходят свои RNN и LSTM аналоги в большинстве конфигураций, будучи гораздо меньше по числу параметров. Исследование предлагает, что Жидкие нейронные сети это конкурентный выбор архитектуры нейронных сетей, особенно когда временная составляющая важна для прогнозов, однако необходимо дальнейшее исследование на более сложных базах данных.

# Medical Image Classification using Liquid Neural Network in Clinical Application

## Introduction

     The modern healthcare sector uses technologies to improve patient outcomes and accelerate the recovery process. A key element of medical interventions involves the use of biomedical images, which play a crucial role in enabling more precise diagnoses and developing effective treatment strategies. However, the interpretation of such images is susceptible to human error, which can result in negative outcomes such as incorrect treatment selection and delayed disease detection. The integration of deep learning techniques has significantly enhanced the accuracy of image analysis by identifying potentially problematic cases for further review by healthcare professionals. These advanced methods have changed the approach towards analyzing and interpreting biomedical data and they provide with automated frameworks that help in the identification of diseases.

     In recent years, the field has experienced rapid advancements in deep learning technologies. Besides other popular approaches that have emerged, the application of Liquid Time-Constant Neural Networks stands out as a promising possibility to enhance the accuracy and efficiency of medical image analysis. First, they were introduced by (Hasani et al, 2021) and now they could serve as a replacement to traditional recurrent neural networks or aggregated output of linear layers when analizing sequential data. Inspired by the dynamic behavior of liquid systems, LNNs are offering a unique framework that utilizes adaptive and self-organizing neural layers to make predictions. This term work shows the potential of Liquid Neural Networks as a new deep learning technique, with a specific focus on their application to the analysis of diverse medical data. The main advantage of LTC is that they have significantly less parameters than other RNNs. The main focus of the term paper is to train relatively compact networks, and assess how LTC works in comparison to the other methods. Then they will be compared to the benchmark’s models, which have significantly more parameters. This study contributes to the current literature about Liquid Time-constant networks, classification of medical images and processing time-series data.

     For the analysis I used standartized MedMNIST datasets to conduct the experiments. The utilization of the MedMNIST datasets serves as an initial step, providing with a great source of medical image data for training and validating neural network models. MedMNIST collection of images contain 6 different 3D image sets to train a model on, such as AdrenalMNIST3D and VesselMNIST3D and etc. The images already have been preprocessed, and they are ready to be used. The sizes of the datasets are relatively small and it is possible to perform the analysis without the need for significant computational resources. Another advantage of the datasets is that they are widely used, and there are some solid benchmarks to compare the results with. Overall, the datasets allow to conduct fast experiments on the data to compare the quality of different architectures.

## Literature review

     The exploration of liquid neural networks in various fields is a show their adaptability and effectiveness. They perform better, than incremental approaches, when sudden changes occur in data patterns (Ayoub et al, 2024). In contrast to them, liquid neural networks have shown the capability of self-adapting to abrupt changes without needing any retraining. Furthermore, liquid neural networks also managed to remove complex, noisy signals derived from the aircraft's magnetic sources, resulting in a significant reduction in aeromagnetic compensation error (Nerrise et al, 2024). This indicates the potential of this machine learning approach to extract reliable and accurate signals from the noise. Lastly, liquid neural networks have also been applied in the field of communication networks to reduce the overhead in urban area, which allowed to dynamically adjust beams to improve connection for mobile users. This also shows the capabilities of the LTC networks to work with noisy data (Zhu et al, 2024).

     As it was previously mentioned, liquid time constant networks utilize adaptive and self-organizing neural layers to make predictions. However, there were major improvements to the algorithm. One of the most important ones are Neural circuit policies principles (Lechner et al, 2018, 2020), which can be applied to the LTC networks. NCP networks are constructed from LTC neurons and differentiate from the normal Liquid networks with a different wiring diagram. The networks are inspired by the nervous system on a living organism and they allow to create sparsely-connected interconnected neurons.

     Another novelty is continuous-time liquid neural networks (Hasani et al, 2022), which significantly improve training and inference time since they eliminate the need for complex numerical solvers. And, as another class of liquid networks, they also demonstrate better performance in time-series modelling, than advanced recurrent neural network models.

## Data

This thesis is based on a publicly available dataset originally designed to explore cognitive responses—specifically confusion—in students viewing online educational video content. The data were collected under controlled experimental conditions, with the aim of studying how EEG signals reflect varying levels of cognitive load during learning.

The dataset includes recordings from ten college students, each of whom viewed a set of ten distinct educational videos. These videos were selected and categorized prior to the experiment into two groups:

* Non-confusing: Topics presumed to be familiar and readily understandable to the average student, such as introductory algebra or geometry.
* Confusing: Advanced topics such as quantum mechanics or stem cell research, selected for their potential to induce confusion in students unfamiliar with the material.

All students watched the same ten videos, evenly split between the two categories. Each video was approximately two minutes long, but only the central one-minute segment was used for EEG data analysis. The beginning and end of each clip were trimmed to minimize transitional and non-content-related cognitive responses.

EEG signals were recorded using a single-channel wireless EEG headset positioned to monitor activity over the frontal lobe. The headset recorded data using one electrode on the forehead and two reference electrodes placed near the ears. The device sampled neural activity every 0.5 seconds, resulting in approximately 120 EEG samples per video per participant.

Each EEG sample consists of power values across multiple standard brainwave frequency bands:

* Delta
* Theta
* Alpha1, Alpha2
* Beta1, Beta2
* Gamma1, Gamma2

These eight channels were the sole features used in this study. All other available information—such as participant demographics or specific details about the videos—was excluded from the analysis. The objective was to evaluate confusion purely from the perspective of neural signal data.

The primary label used in this thesis is the predefined confusion label, assigned based on the categorization of each video as either “confusing” or “non-confusing.” This classification was made independently of the participants' self-assessments and remains consistent across all viewers. The use of this label enables an investigation into whether confusion—operationalized at the video level—can be predicted from EEG features alone.

The dataset comprises over 12,000 EEG samples, corresponding to 100 individual recording sessions (10 participants × 10 videos). Each sample includes:

* A timestamp (0.5-second intervals)
* Eight EEG frequency band values (delta through gamma2)
* The predefined confusion label (binary)

These data were used to develop and evaluate predictive models aimed at distinguishing between confusing and non-confusing learning experiences based solely on patterns in brainwave activity.

## Methodology

### Training setup

     The models in this study were trained using only EEG-derived features—specifically, the power values across eight standard frequency bands: **delta, theta, alpha1, alpha2, beta1, beta2, gamma1, and gamma2**. No participant demographic data or video metadata were included. This design choice allowed for an isolated exploration of how neural signals alone relate to cognitive confusion.

Each EEG time series corresponds to a one-minute segment, sampled at 0.5-second intervals, resulting in up to **120 time steps** per recording. To ensure consistency across samples, each sequence was **padded to a fixed length of 144 time steps**, using zero-padding at the end of each signal. This allowed all models to accept uniform input dimensions while preserving the temporal structure of the original signals.

The dataset was split into training and testing subsets using a **70–30 ratio**. To ensure robust and reliable evaluation, **multiple distinct and fixed data splits** were created. All models were trained and evaluated on the same series of partitions, ensuring comparability across experiments while mitigating the effect of variance due to random sampling. Each model was trained for the **same number of epochs**, standardizing training duration across all experiments.

In some experiments, a **lagged embedding** of the EEG signal was applied to enrich the input with temporal dependencies beyond the original sampling rate. This involved concatenating delayed versions of the input signal to provide the models with access to past temporal context within a given time window.

### Quality metrics

Model performance was assessed using a combination of three evaluation metrics:

* Accuracy: Measures the proportion of correctly classified samples out of all predictions.
* AUC (Area Under the Receiver Operating Characteristic Curve): Evaluates the trade-off between true positive and false positive rates across thresholds, providing a robust metric for binary classification.
* Entropy: Used as a measure of prediction uncertainty. Lower entropy values indicate higher confidence in model predictions, and this was used to assess model sharpness across experiments.

All metrics were averaged across the multiple fixed splits to obtain reliable, variance-reduced estimates of model performance.

### Models

The predictive models employed in this work consisted of three major types of neural network architectures, each with multiple internal variations:

* GRU-based networks: These models leveraged Gated Recurrent Units, which are well-suited for capturing temporal dependencies in sequential data while maintaining a relatively compact architecture. Several variations were tested with different numbers of layers and hidden dimensions.
* LSTM-based networks: Networks built with Long Short-Term Memory units were also explored due to their effectiveness in retaining long-range dependencies and mitigating vanishing gradient issues. As with the GRU models, multiple architectures were tested.
* Liquid State Neural Networks (LSNNs): Inspired by biologically plausible models, these networks incorporate liquid time-constant dynamics, allowing them to adapt their memory and response patterns over time. LSNNs were included to investigate whether models with non-static internal dynamics could outperform more traditional RNN variants on EEG time series data.

In each category, a range of architectures was evaluated to explore the design space and identify the most effective configurations for confusion detection.

All hyperparameters—including learning rate, batch size, number of layers, and hidden unit size – were manually selected based on preliminary testing and domain knowledge. These settings were held constant across similar models within each experimental group to ensure fair comparisons.

### Experimental Results

## Conclusions

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