Rheological characterization of non-Newtonian fluids using Deep CNN

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Introduction

The viscoelastic properties of cells are hard to characterize in absence of a standard model. Recently, deep learning has been proposed as a tool for qualitative comparison between similar cell types based on deformation [1]. The biggest challenge when it comes to working with live biological cells is the limited availability of data. Fluid droplets, however, offer a suitable alternative to droplets. Cells can be modeled as complex droplets and their deformation characteristics are similar to that of droplets. In this work, we used droplets in lieu of live biological cells. The characteristics of deformation and subsequent shape recovery of droplets are correlated to their rheological properties. Therefore, a deep learning model capable of classifying fluids based on their rheological properties can be extended by transfer learning to learn rheological properties of biological cells. This is the motivation behind this work. In this work, we use deformation characteristics of droplets of varying rheological properties to classify non-Newtonian fluids. We developed a simple CNN model and trained it on sequential data of droplet deformation. We compared the performance of the CNN model with recurrent neural network models which are designed to handle sequential information. Specifically, we used a simple RNN model, a GRU and an LSTM model.

Dataset

Data was collected by imaging deformation of droplets of different fluids at the constriction of a microfluidic hyperbolic channel (Fig 1A). The fluids used here were DI water, 0.1% and 0.25% methylcellulose. The fluids have distinct viscoelastic properties. Therefore, their deformation and relaxation characteristics are also different. The raw data consists of several droplets entering the hyperbolic channel (Fig. 1B). Using the image processing toolbox in MATLAB, we overlayed the image of a single droplet at 4 time instants onto a blank frame (Fig. 1C). This generated 125x25 images containing sequential information of droplet deformation and subsequent relaxation. For the recurrent neural network, we converted the images of droplets at four instants into arrays of size (N, 4, 650) where N is the number of examples (N = 12,751), 650 is the number of features.

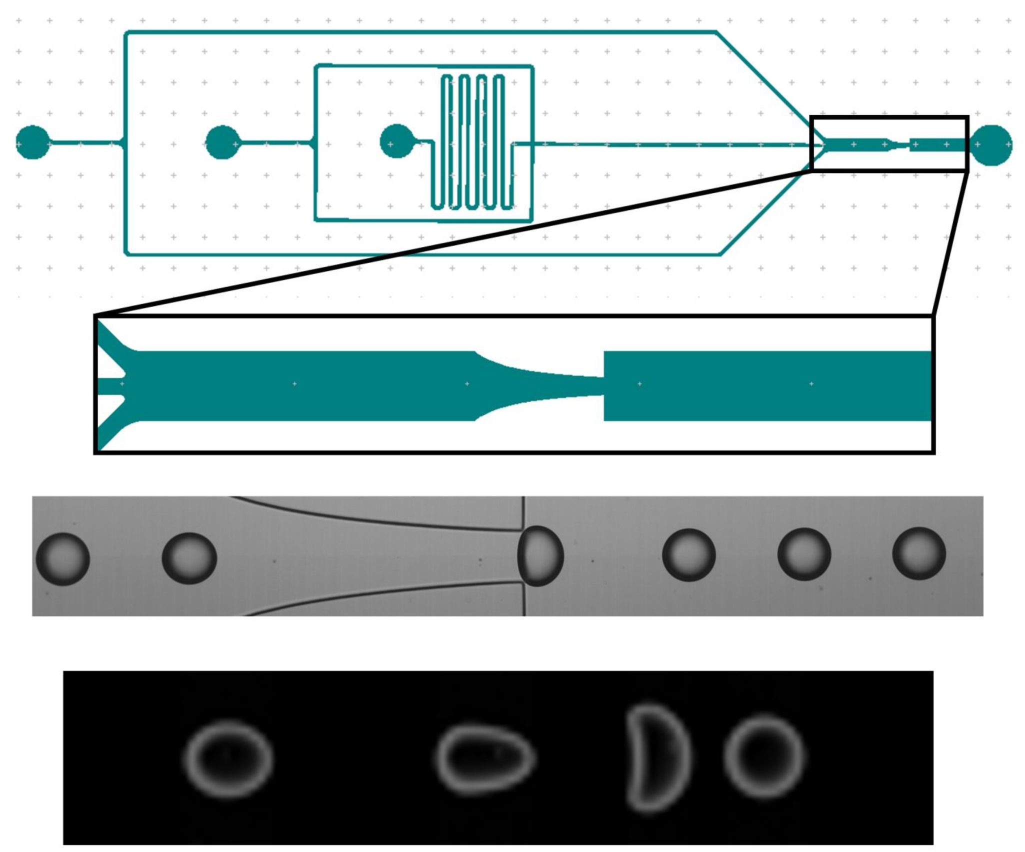

Fig 1. Data generation and processing

Results

Deep CNN

The architecture of the CNN model used here is as follow:

Input ⟶ ConvBlock1 ⟶ ConvBlock1 ⟶ ConvBlock2 ⟶ ConvBlock2 ⟶ FC (3) ⟶ Output

The ConvBlock1 consisted of a Conv layer, BatchNorm, Dropout, ReLU and MaxPool. The ConvBlock2 consisted of a Conv layer and batch normalization. Hyperparameter tuning was performed to optimize the performance of the model and avoid overfitting. The model had an accuracy of 82% for a two-class problem. But the accuracy dropped to 60% when a third class was introduced. This suggests that the model suffered from a large bias. Saliency map (Fig. 2) shows that the model was able to learn to classify based on the shape of the droplets. However, further pre-processing of the training data may be needed to boost prediction accuracy.

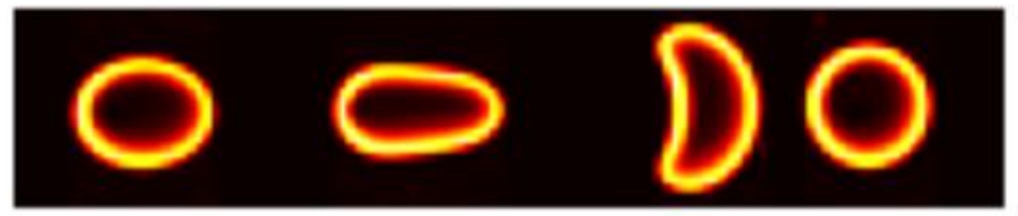

Fig 2. Saliency map from the CNN model

Recurrent Neural networks

The recurrent neural network architecture used here is as follows:

Input ⟶ BatchNorm ⟶ Rec block (256) ⟶ Rec block (256) ⟶ FC (24) ⟶ FC (3) ⟶ Output

We used three different Rec blocks: Simple RNN, GRU and LSTM. The models were optimized to prevent overfitting by applying L2 and dropout regularization. However, the test accuracy of these models were found to be quite low with 47% being the highest accuracy obtained on the GRU model.

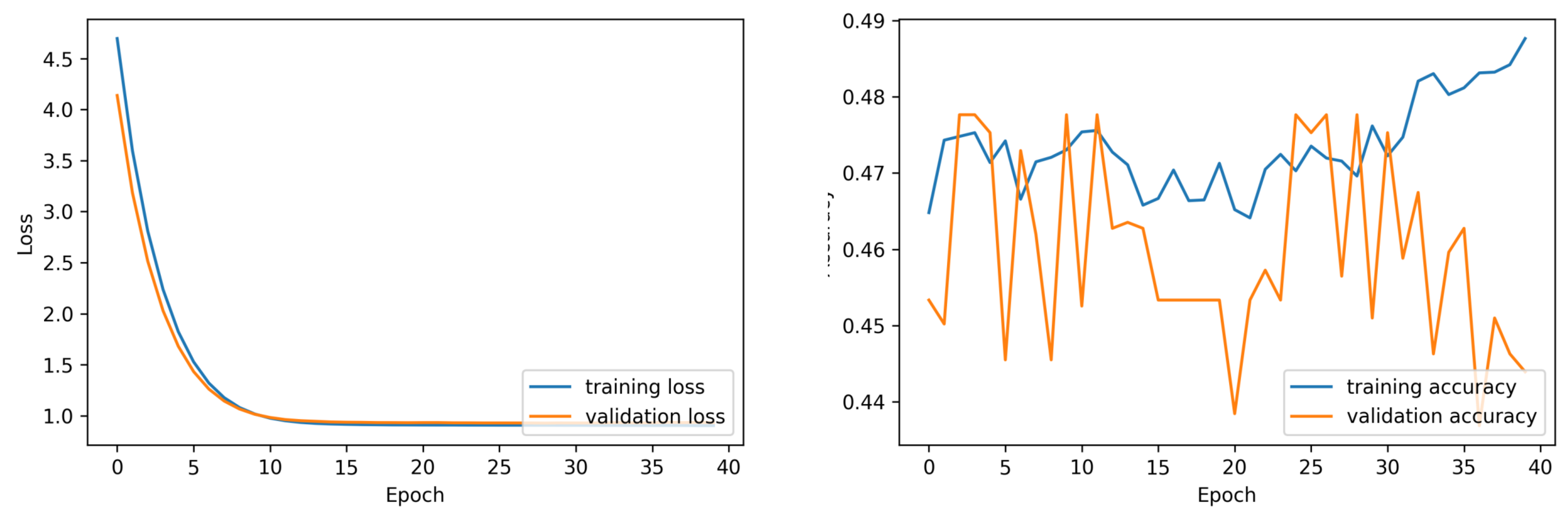

Fig. 3. Performance of the LSTM model: Loss (left) and Accuracy (right)

Results

The recurrent neural network seems to perform equally worse with GRU achieving the highest test accuracy of 47%

Table 1. Comparison between the recurrent neural networks

Model (%)	Train (%)	Validation (%)	Test (%)
Simple RNN	52.53	46.82	45.53
LSTM	51.24	45.73	46.16
GRU	49.01	46.20	47.41

Conclusion

The CNN model was found to perform slightly better than any of the recurrent neural networks with an accuracy of 60% as opposed to 47% achieved in the GRU model. However, the accuracy of prediction is still quite low. This seems to indicate a high bias in the model. To reduce bias and improve accuracy, the input data may be needed to be processed further. Hybrid recurrent networks such as CNN-GRU and CNN-LSTM may perform better than the recurrent networks used here.

References

[1] Cody Combs, Daniel D. Seith, Matthew J. Bovyn, Steven P. Gross, Xiaohui Xie, Zuzanna S. Siwy, "Deep learning assisted mechanotyping of individual cells through repeated deformations and relaxations in undulating channels", *Biomicrofluidics*, 2022.

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