

# PHYTOLITH CLASSIFICATION USING DEEP LEARNING: IMPLEMENTATION OF A U-NET NEURAL NETWORK FOR MORPHOTYPE IMAGE-SEGMENTATION

Nafsika C. Andriopoulou, Georgios Petrakis and Panagiotis Partsinevelos  
Technical University of Crete, School of Mineral Resources Engineering, 73100 Chania Greece

## Introduction

- Phytoliths constitute microscopic plant biominerals of high importance to geosciences and archaeology, and their analysis contributes significantly to the identification and study of plant remains in soils/sediments and artefacts [1]
- Automatic classification of phytoliths may enhance data homogeneity among researchers worldwide and facilitate reliable comparisons
- A «fully convolutional network» (FCN) architecture was implemented to classify phytoliths extracted from modern wheats (*Triticum* spp.) using the dry method

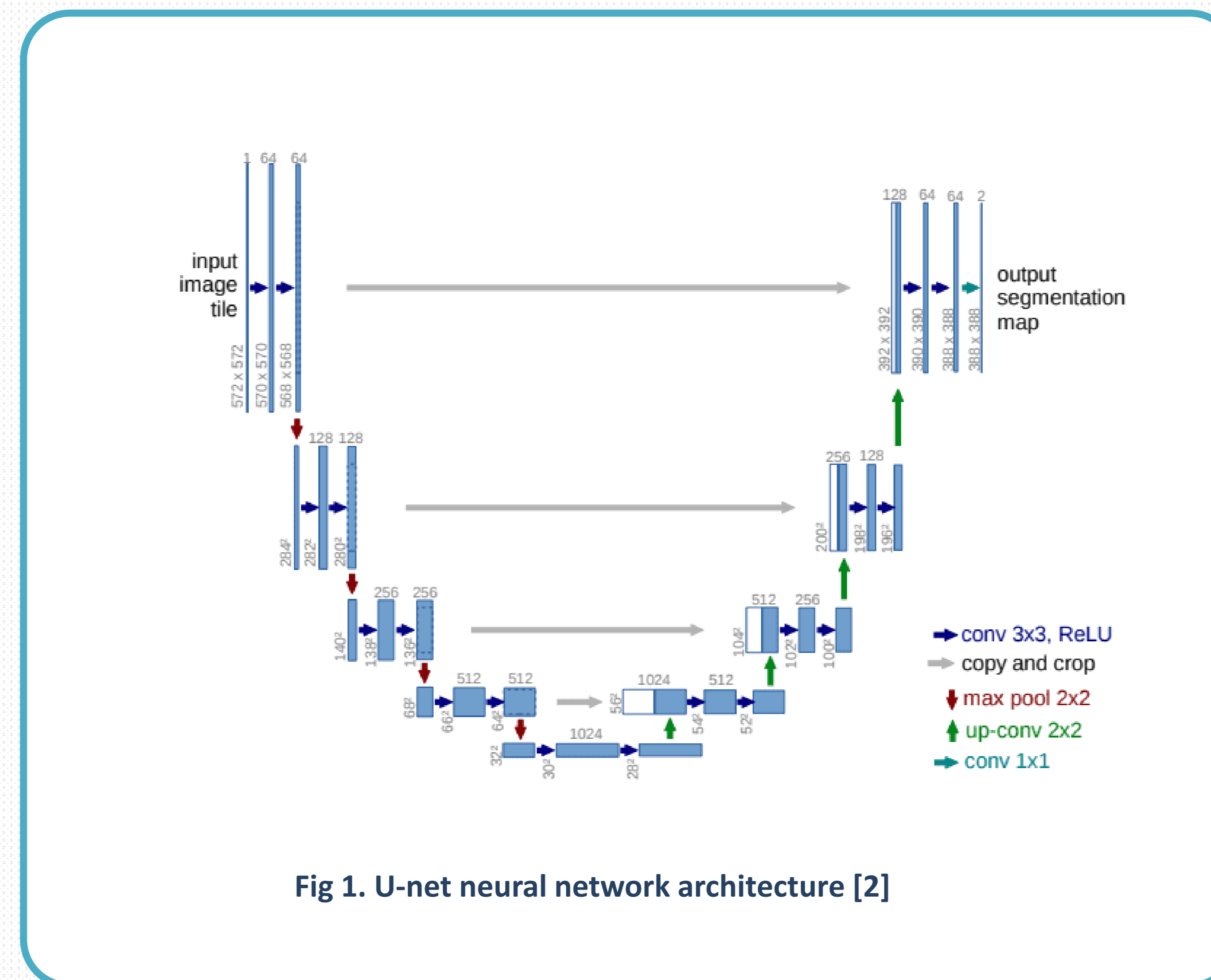
## Research challenges

- Traditional phytolith classification is usually a time-consuming process and may coherent human observer biases
- The free available image **datasets of phytoliths** are crucial for the learning process of neural networks
- In the **present study**, we propose an image-segmentation methodology based on deep learning, which is able to detect four morphotypes: (a) **Stoma**, (b) **Rondel**, (c) **Papillate**, and (d) **Elongate dendritic**

## Materials & Methods

- Phytoliths are typically classified by their morphological characteristics (e.g. shape), the plant taxon and/or the anatomical plant part where they are formed
- Photomicrographs of phytoliths were acquired using optical microscopy (Fig. 2b), and morphotypes, morphologically unaltered at the highest possible level, were identified based on the standard literature
- The photomicrographs were further manually annotated forming four classes of morphotypes linked to different anatomical plant parts (i.e. leaves, stem, and inflorescence)
- A dataset of 250 pairs of images (images/annotations) was splitted in training, validation and testing set with a percentage of 70 - 15 - 15 % respectively
- The dataset feeded a **fully convolutional neural** network with the aim of learning and subsequently detecting and localising the four classes of phytoliths using image-segmentation
- A U-net (Fig. 1) architecture was implemented because of its high efficiency in small size of the datasets [2]

## The neural network architecture



The U-shaped model of U-net is divided in two main parts:

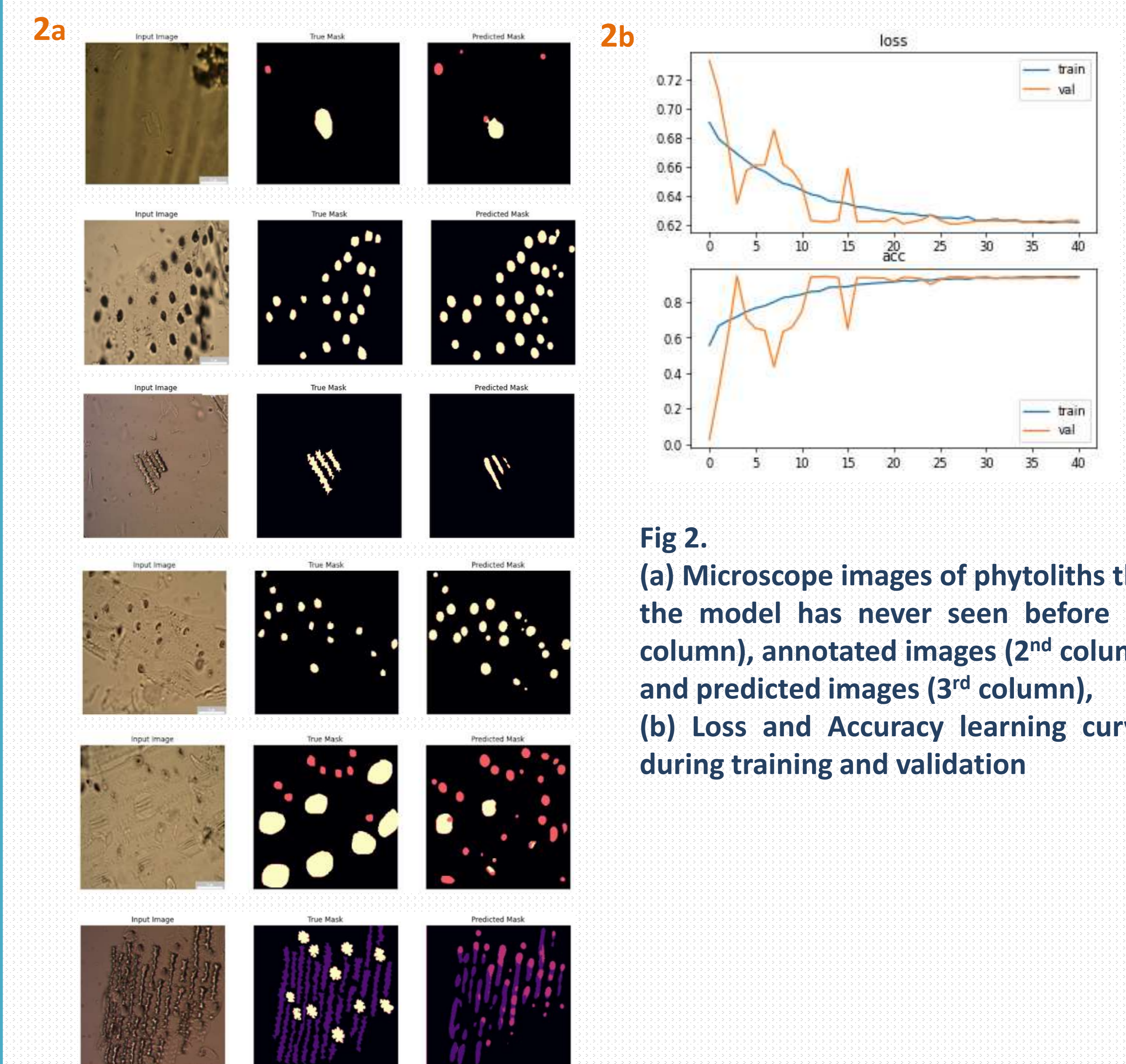
- The encoder [left side of the network (Fig.1)] which downscales the images, increasing the feature maps and learns from the content of the training dataset
- The decoder [right side of the network (Fig.1)] which upscales the images, decreasing the feature maps and conducts precise localisation of the detected phytoliths

## Model basic (hyper)parameters

- Loss function: Dice loss
- Optimizer: Adam
- Learning rate: 0.001
- Epochs: 41
- Metrics: Accuracy, Intersection over Union (IoU)

## Results

The model is able to predict four classes of phytoliths with validation accuracy 93% and IoU 86%



## Conclusions

- A novel implementation of deep learning in phytolith classification and image segmentation is proposed
- The trained model is able to detect the four classes of phytoliths in the evaluation (testing) dataset and succeed high accuracy given the small dataset that was used
- The present dataset is promising for building up the capacity of phytolith classification within unfamiliar datasets from archaeological contexts

## References

- [1] Piperno D.R. (2006) *Phytoliths. A comprehensive guide for archaeologists and paleoecologists*. Lanham: AltaMira Press  
 [2] Ronneberger O., Fischer P., Brox T. (2015) U-Net: Convolutional Networks for Biomedical Image Segmentation. In: Navab N., Hornegger J., Wells W., Frangi A. (eds) *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015*. MICCAI 2015. Lecture Notes in Computer Science, vol 9351. Springer, Cham. [https://doi.org/10.1007/978-3-319-24574-4\\_28](https://doi.org/10.1007/978-3-319-24574-4_28)