Classifiying Transmission Electron Microscopy Virus Textures

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Abstract

Determining the identity of a virus sample is of utmost importance in today's medical community. An incorrect classification of the virus can be life-threatening not only to the patient, but to people surrounding him or her. A transmission electron microscopy image of a virus sample can be hard to discern for the human eye and a doctor needs to be positive about the identity of the virus i.e., if it's Influenza or Ebola. Fortunately, machine learning algorithms perform exceedingly well on image classification tasks and don't require expert knowledge to do so. Here we present a successful application of using convolutional neural networks to classify viruses samples into one of 15 categories and compare its performance to previous work done on the same task.

1. Introduction

2. Related Work

In the work of Kylberg et al. [1], texture analysis is performed on the virus samples and the resulting feature vector is fed to a Random Forest classifier. They are comparing the performance of different texture analysers such as Local Binary Patterns and Radial Density Profile along with their respective variants. First, we will briefly explain the feature extractors they used. Then, we will present the results they got.

2.1. Local Binary Profile (LBP)

Given an image, for each pixel p_i in it, sample n equally-spaced points on the circle of radius r with center p_i – an example of sampling is shown in figure 1 – and construct a vector $v(p_i)$ such that its ith entry is a 1 if the ith sampled pixel has a value bigger than p_i or a 0 otherwise. With its sequence of 0s and 1s, $v(p_i)$ now makes a binary number v_{p_i}, hence the name. Once we have the v_{p_i} for all pixels, we construct a histogram counting the number of appearances of each value v_{p_i}. The histogram is the feature vector associated with the given image. Kylberg et al. [1] denote this feature extraction method by $\mathrm{LBP}_{n,r}$, where n is the number of sampled points and r is the radius, as described above. The resulting histogram is represented in a vector of counts with 2^n elements.

Rotational Invariant LBP In order to reduce the size of that feature vector, Kylberg et al. [1] mention a modification of LBP in the following sense: instead of creating v_{p_i} by interpreting the vector $v(p_i)$ and using v_{p_i} as is, rotate the number v_{p_i} bitwise until you get the smallest possible number. For example, the number 110 would turn into 011. They name it rotational invariant and denote it with $\mathrm{LBP}^{\mathrm{ri}}_{n,r}$.

Uniform LBP To further reduce the size of the histogram, they also try restricting the values of v_{p_i} to only numbers that have 2 or less transitions from 0 to 1 or from 1 to 0 and they call this variant *uniform binary patterns with at most 2 spatial transitions*, denoted $\mathrm{LBP}^{\mathrm{u2}}_{n,r}$. For example, 01010 has 2 transitions from 0 to 1 and 2 transitions from 1 to 0 which makes 4 transitions in total so this version $\mathrm{LBP}^{\mathrm{u2}}_{n,r}$ would not

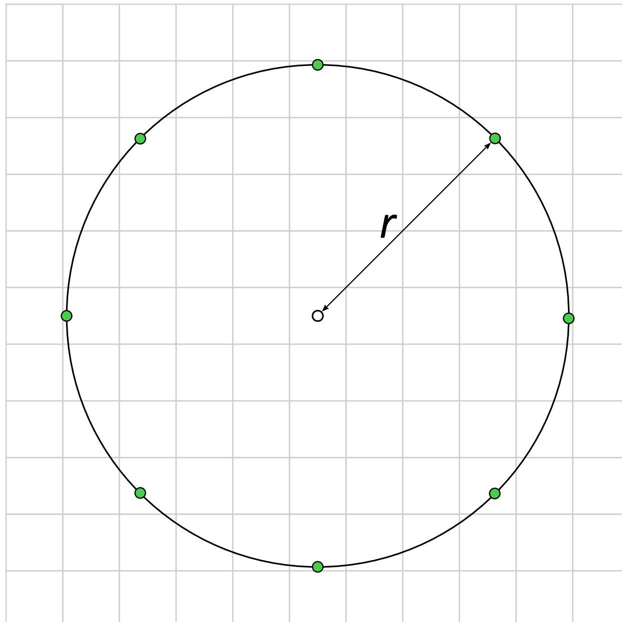

Figure 1: Example of LBP sampling: The green points are the neighbouring sample points at distance r from the central white point. In this case, we are sampling with $n = 8$ neighbour points.

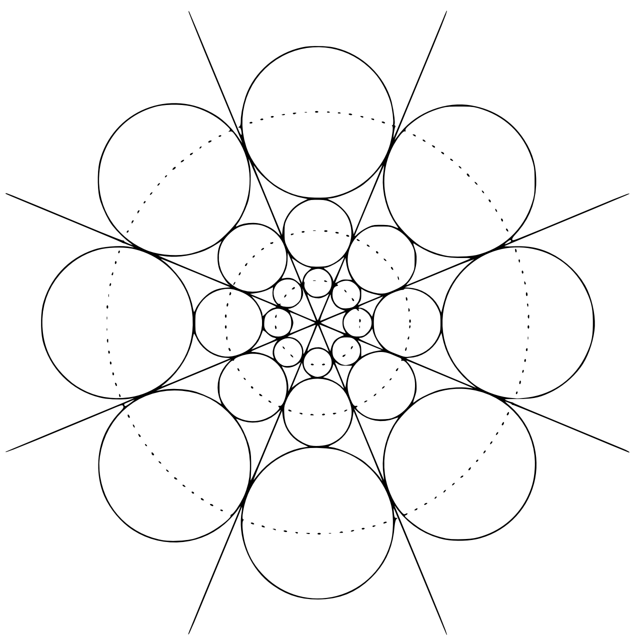

Figure 2: Example of LBPF sampling: In the simple LBP, the points would be sampled at equal distances around the dotted circles for one radius as in figure 1 but with this extension, the points are sampled according to a Gaussian distribution inside the solid black circles at multiple radii. In this picture, the number of neighbours also vary with the radii. This image comes from Mäenpää and Pietikäinen [2].

count that number. On the other hand, 00111 has only 1 transition from 0 to 1 so it is accepted.

Gaussian Filtered LBP Finally, Mäenpää and Pietikäinen [2] talk about an extension to the LBP that is also used in the work of Kylberg et al. [1] which consists in sampling the neighbours at different radii around the central pixel. Additionally, instead of sampling on circles with points spread in an equidistant fashion, they would be sampled according to a Gaussian distribution. Figure 3 shows an example of such a sampling. Kylberg et al. [1] denote it as $\mathrm{LBPF}^{\mathrm{ri}}_{n_1,r_1} + {}^{\mathrm{ri}}_{n_2,r_2} + \cdots + {}^{\mathrm{ri}}_{n_j,r_j}$ for the different numbers of sample points $n_1, n_2, \cdots, n_j$ and different radii distances $r_1, r_2, \cdots, r_j$.

2.2. Radial Density Profile (RDP)

This method is a way to get the mean intensity in a ring around each pixel in the image. Kylberg et al. [1] defines the *radial mean intensity* f around a center pixel q_c as

$$f(q_c, r) = \frac{1}{|N|} \sum_{q \in N} I(q)$$

where $I(q)$ is the pixel value for pixel q and $N = \left\{q : \|q - q_c\|_2 \in \left(r - \frac{1}{2}, r + \frac{1}{2}\right]\right\}$ is the set of pixels in a ring around q_c of width 1 at distance r from q_c. Figure 3 shows an example of what the set N may look like. Following the notation from Kylberg et al. [1], let $\bar{f}_{q_c}$ be the mean of the set $\{f(q_c, i)\}_{i=1,\cdots,n}$. Then they define the radial density profile for that pixel q_c as $\mathrm{RDP}_n = \left[f(q_c, 1) - \bar{f}_{q_c}, f(q_c, 2) - \bar{f}_{q_c}, \cdots, f(q_c, n) - \bar{f}_{q_c}\right]$.

It is not explained how the pixel features are combined to make the feature vector for the whole image but we would imagine that the feature vector for the whole image is either a concatenation of the pixel features or the concatenation of the mean of each pixel feature.

Fourier RDP One variation Kylberg et al. [1] introduced is applying the same RDP technique on the image after it undergoes a Fourier transform and looking at it with respect to a base e logarithmic scale. They denote it with FRDP_n.

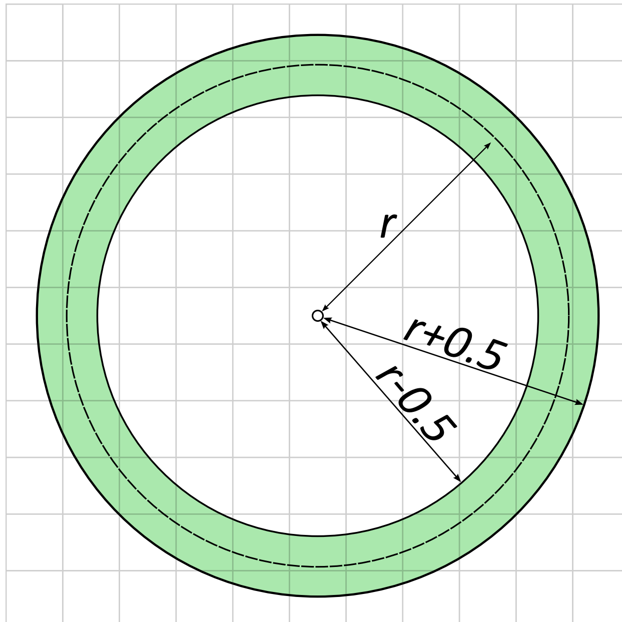

Figure 3: Example of RDP sampling: The green zone is the set of sampled pixels for a given radius r.

References

[1] Gustaf Kylberg, Mats Uppström, and Ida-Maria Sintorn. Virus texture analysis using local binary patterns and radial density profiles. In *Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications*, pages 573–580. Springer Berlin Heidelberg, 2011.

[2] Topi Mäenpää and Matti Pietikäinen. Multi-scale binary patterns for texture analysis. In *Image Analysis*, pages 885–892. Springer, 2003.