Executive summary

Aurora has over 15 years’ experience providing leading edge software into the image recognition market; recent investments in artificial intelligence and particularly deep learning capabilities have enabled the development of an accurate, automated solution for diagnosis of cancer (though detection of mitosis in histopathology images) within 12 weeks. The accuracy of Aurora’s solution has been measured against the results obtained by leading organisations, in a recent assessment; the Aurora solution is demonstrably the most accurate. This paper outlines the challenge, Aurora’s approach and the results obtained.
Problem definition
Mitosis count is one of the most common techniques used by physicians to assess the presence of cancer. The aim of this project is to design a system that detects mitosis in images of human tissue, in particular breast tissue. The system is wholly implemented using the deep learning technology and framework developed at Aurora.

Detail
A system has been implemented for the localisation of image patches containing mitosis in standard histopathology images. The AI created scans across each pixel in an image and assigns the location to one of two classes: mitosis present; or mitosis absent. An example of the system output is shown below, in which the single instance of mitosis present has been accurately and correctly located towards the bottom right corner.

The AI was created using Aurora’s Deep Learning technology, in particular Convolutional Neural Networks via Aurora’s Artificial Intelligence SDK. The system is accurate at localising mitosis at a low rate of false positives. In this field, the commonly used value to assess performance of the system is the F2-measure (a summary figure taking into account both False Positives and False Negatives) and this shows results comparable with the best results reported for this problem in the prestigious MITOS challenge.

Training Data
To create the AI, it must be trained using a collection of suitable training images. In this project this includes histopathology images from the MITOS challenge. Histopathology images are images of tissue that have been taken under the microscope and are stained to enhance visualisation of cellular structure. The training images have been manually labelled by an expert pathologist.
An example of the MITOS challenge images is shown above. The yellow dot shows the location where a mitosis is present. Mitosis locations are provided as a text file, indicating the location (or absence) of mitosis in each images. Correctly labelled training images are essential for training of an Artificial Intelligence.

**Training the Artificial Intelligence**

Aurora used its deep learning platform to create the AI capable of accurately locating mitosis in histopathology images. The deep learning system is fed with small image patch samples of mitosis and non-mitosis as shown below.

Using these patches, sourced from 10,000 example histopathology images, the Deep Learning system is able to create a neural network capable of finding specific image features, shapes and colours that accurately indicate the presence of mitosis in an image. This is very similar to how a human expert would learn to detect such features. The advantage being that an AI can analyse far more images than a human could in a lifetime of experience.
Testing

In order to assess the efficacy our system, we have used the MITOS challenge protocol. This consists of calculating the “F2 measure”; a single performance rating that takes into account both the recall and precision of the system, presenting a suitable balance of False Positives and False Negatives, as shown below.

\[
F2\text{ Measure} = \frac{2 \times (\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})}
\]

Where:

- **True Positives (TP):** Number of correctly detected mitosis.
- **False Negatives (FN):** Number of mitosis that were not detected by the system.
- **False Positives (FP):** Number of locations incorrectly classified as mitosis.

\[
\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}
\]

\[
\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}
\]

Results are computed on a blind test-set of histopathology images. All images in this set are submitted to the AI, which returns the location and probability of a mitosis. The MITOS challenge publishes the results based on this F2 measure, which we have taken as a comparison to Aurora’s results below.

<table>
<thead>
<tr>
<th>Organisation</th>
<th>F2 Measure</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aurora</td>
<td>0.386</td>
<td>Most accurate</td>
</tr>
<tr>
<td>CUHK (MITOS challenge)</td>
<td>0.356</td>
<td></td>
</tr>
<tr>
<td>MINES-CURIE-INSERM (MITOS challenge)</td>
<td>0.235</td>
<td></td>
</tr>
<tr>
<td>YILDIZ (MITOS challenge)</td>
<td>0.167</td>
<td></td>
</tr>
<tr>
<td>STRASBOURG (MITOS challenge)</td>
<td>0.024</td>
<td>Least accurate</td>
</tr>
</tbody>
</table>
Further Examples of Aurora’s Results

In the example below, the thin green circles are manually labelled by human experts as non-mitosis locations that appear like mitosis and therefore represent areas of difficulty where an automatic system would likely be confused; however as can be seen, the Aurora AI correctly rejects all of these regions.

Some false positives and false negatives do occasionally occur, as with any automatic system (or human expert) but the level of detection can be adjusted by setting suitable threshold values. For instance, to tip the balance towards the likelihood of false positives rather than false negatives, ready for human confirmation by highlighting areas of uncertainty.