**Early detection and classification of live bacteria using time-lapse coherent imaging and deep learning**

Identification of pathogenic bacteria in food, water, and bodily fluids is important, but it is challenging because of the complexity of samples and the large volumes that need to be screened quickly. The live microscopy images of bacteria growth in a 60 mm diameter agar plate every few seconds and uses deep neural networks to detect bacterial growth and classify the species. A time-lapse imaging platform uses two different deep neural networks (DNNs). The first DNN is used to detect bacterial growth as early as possible and the second DNN is used to classify the type of bacteria growing based on the spatiotemporal features obtained from the coherent images of an incubated agar plate. The system was demonstrated by quickly detecting Escherichia coli and total coliform bacteria. This method can detect pneumonia in water samples much sooner than the EPA-approved methods, which can shorten the detection time by more than 12 hours. The Process has the following approach Design and training of neural networks for bacterial growth detection and classification, Blind testing results for the early detection of bacterial growth, Blind testing results on the classification of growing bacteria and the last Limit of detection as a function of the total test time.   
The Result of the method was that the system was able to detect a colony-forming unit (CFU) in ≤9 hours of total test time using the preincubation of samples in growth media. And this platform is very economical (~$0.6 per test) and has high performance with a scanning speed of 24 cm2/min across the entire surface of the tablet, making it very suitable for integrating with existing methods that are currently used to detect bacteria on agar dishes.

**Monitoring biofilm function in new and matured full-scale slow sand filters using flow cytometric histogram image comparison (CHIC)**

In this method bacteria in inflows and outflows from full-scale SSF were investigated using flow cytometry (FCM) using cytometry histograms. Image comparison (CHIC) analysis; Heterotrophic organisms, total coliforms, and routine microbial counts of E. coli. To see if FCM can measure the effectiveness of biofilms, different SSFs were compared based on their age and sand composition. Fcm profiles cannot be separated from two default filters. To examine the biofilm in the deep sand bed, Ssf was detected during a scrapping event when the top layer of sand and the top layer of sand was Schmutzdeck removed to restore flow through the filter. The method follows the approach at first Samples were collected from a sterilized borosilicate bottle one day before, and up to three weeks after, the scraping of each SSF. The data were analyzed according to the day of the scraping, with day 1 being the day before scraping, day 2 being the day of the scraping activity, and so forth, and then Water samples for conventional microbial parameters were processed by the treatment plant staff according to a routine schedule and coincided in time with the flow cytometry analysis after that FlowJo software was used to process and gate data. Signals were collected and analyzed by using a gate to filter out green light (FL1, 533 ± 30 nm) and red light (FL3, >670 nm). Gating was done following the gating strategy described in (Prest et al., 2013) and the gating was identical for all samples. The green fluorescence histogram plot is called the fluorescent fingerprint. The percentage of bacteria with low nucleic acid content (LNA) and bacteria with high nucleic acid content (HNA) was determined as described in Prest et al. (2013). Statistical analysis was performed on all data using one-way ANOVA, followed by the Tukey test in R.

The result of the method defines the stability of an SSF was unchanged by scraping: total organic carbon (TOC), pH, numbers of heterotrophs, coliforms, E. coli, and FCM bacterial profile were all unaffected. However, the performance of two new SSFs containing new and mixed sand was compromised breakthrough of both microbial indicators and TOC occurred following scraping. The new SSFs exhibited reduced performance, and this was reflected in distinct communities of bacteria in the effluent. The presence of microbial indicators correlated to the community of bacteria in the influent. This study showed that FCM can monitor SSF performance. The removal of the top layer of sand did not change the effluent water from the established SSFs but did affect the effluent water from the SSFs containing new sand. The impact of surface biofilm on effluent water is greater when the deep sand bed biofilm is not present.

**Dynamic batch size tuning based on stopping criterion for neural network training**

Many researchers and engineers engaged in both basic and applied research in the field of neural networks are intrigued by the concept of deep learning. Several studies have proposed more efficient models and algorithms to increase the training quality of neural networks, while others have theoretically solved the black box concerns associated with neural networks. The paper examines the transition between the loss function value and prediction accuracy to see how beneficial the proposed strategy is. On a number of benchmark datasets, we compare the proposed method to established batch size-increasing algorithms based on linear and step functions, using multilayer perceptron (MLP) and convolutional neural networks (CNNs). The focus of this study is on batch size, or the number of samples included in a minibatch during neural network training. It has an effect on computing cost and training performance, according to researchers. The batch size or timetable for altering the size is frequently fixed during training, which reduces generalization performance in the same way that other hyper-parameters do.

The simulated annealing method, a basic approach for the global optimization issue that allows finding a solution nondeterministically based on the randomization strategy, is typically similar to the strategy of gradually increasing batch size. It shifts a parameter in the direction of increasing function value with the probability set by a temperature parameter that lowers over time. It can be used to find a solution in the early stages of training and can be used to effectively converge on the goal solution in the later stages. The SC method is having the following approach The batch size can frequently be fixed or increased in this section using a step or linear functions. However, the batch size value and method for increasing it are usually determined prior to training and cannot be changed in response to variable training conditions, resulting in poor generalization performance. The convergence of a parameter at an unsuitable local minimum is the main cause of poor generalization performance. A large training loss is not necessarily associated with such a low minimum. Even if the loss is minor, being caught at a sharp minimum leads to poor generalization performance, according to Hochreiter et al., since the sharp minimum has a high sensitivity to loss function fluctuation induced by varied inputs. Later the Algorithm part in which finding out if a parameter is trapped at a local minimum is a difficult task. When this happens, the loss function's change in value tends to be less. We concentrate on introducing an SC that is used to perform early stopping, a strategy that stops the training process in order to minimize overfitting. Training can be halted early if it becomes stagnant, even if the number of epochs set earlier has not been reached. Instead of halting the training process, the SC is used in this study to determine when to reduce the batch size. Various stopping criteria can be considered, but we want to choose one that is appropriate. In an ideal instance, the losses computed based on the test data must be used as an SC in the early stopping procedure. When target labels for the test data aren't accessible, the losses from the validation data are usually used instead. A large generalization loss, according to Prechelt, is one of the candidate reasons to halt training because it immediately signals to overfit. During the next step of the method the experimental setup the batch size varied, and the number of iterations, or parameter changes during one-epoch training, varied among those approaches; specifically, the number was considered minimal in the case of (2). (fix the batch size to Smax). On this premise, we compared the strategies in such a way that the SC-based method did not have an advantage when the maximum accuracy and lowest training loss were compared. For all approaches other than the SC-based method, the highest accuracy and lowest loss until the maximum epoch were always examined, while those until a smaller epoch that did not exceed the minimum number of iterations when employing those methods were evaluated for the SC-based method. When the loss function becomes very unstable and the parameter is updated based on the gradient of the function, the update direction of the neural network parameter varies randomly, as in simulated annealing [21–23]. We chose to present the change in loss function values rather than weights to showcase the effectiveness of destabilization because each weight does not change in the same way. Repeating the destabilization stage helps a parameter to avoid being caught at local minima and converge at a stable minimum, resulting in improved generalization performance. Using a variety of benchmark datasets and neural network models, we illustrate the advantages of the suggested strategy.

The testing results showed that the proposed SC-based method performed better in terms of enhancing test accuracy under various situations than the alternative method based on employing a fixed batch size and other batch size increasing methods based on step and linear functions. Furthermore, the proposed strategy might be successfully used to speed up training and reduce run time. Increasing the learning rate based on the SC, on the other hand, was not as beneficial as reducing the batch size in order to destabilize the loss function.