Analysis of the effect of indoor environment on pupils' health in one Norwegian school during COVID-19 pandemic

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ABSTRACT

The aim of this project is to investigate and predict the quantified effect of indoor environment on pupils' health in schools in Norway during the COVID-19 pandemic.

The results are based on field measurements of the indoor environment in a Norwegian school. In addition, a survey (Mitt Inneklima) from NAAF was given to the pupils, and the result was investigated by using a machine learning model.

From the field measurements it was found that the indoor temperature was generally too high, the relative humidity was too low, and the CO_2-concentration was typically below 1000 ppm.

The survey shows that more pupils are experiencing various indoor climate problems every week compared to the reference school for almost all of the parameters. By using machine learning, it is found that Too hot is an important feature for 11 of the 12 health problems, while Dry air is an important feature for nine of them.

INTRODUCTION

§9 A-2 in the Norwegian Education Act states that "All pupils are entitled to a good physical and psychosocial environment conducive to health, well-being and learning." *Ministry of Education and Research* (1998). Therefore, the schools are obligated to ensure an indoor environment that does nothing to compromise their pupils' health.

The children at primary and lower secondary schools are particularly sensitive to poor indoor climate, since their young, undeveloped bodies have more trouble dealing with the pollutants than an adult body. *Folkehelseinsituttet* (2015a).

The year 2020 has been different from other years, due to the outbreak of the corona virus, SARS-CoV-2. The schools in Norway were closed for a long period last spring, but most of them have been open during the autumn. There have been shorter periods with quarantined pupils and teachers, as well as different and stricter infection control rules than normal.

The school investigated in this study operated at half capacity the last months before Christmas due to COVID-19. Therefore, the amount of pupils in the classrooms were halved during the measuring period. This may change several indoor environment parameters.

Too high air temperature may result in fatigue, dry skin and a lower tolerance for pollutants in the air. If the temperature is too low, the heat loss from the body increases, and the body can be more receptive for infectious diseases. *Utdanningsdirektoratet* (2018).

TEK17 recommend an operative temperature between 19°C and 26°C in the classroom when doing easy work. Another recommendation is that the air temperature should be below 22°C during the heating season. *DIBK* (2017).

Humidity is the amount of water vapor in the air. High humidity can lead to problems with condensation, mould growth, unpleasant odours, mucosal irritation, and a general experience of poor air quality. If the humidity is too low, there can be problems with static electricity, mucosal and eye irritation, dehydration of the skin, and it may increase the risk for respiratory infections. *Becher, Bjerke, Martinsen, & Øvrevik* (2016)

Humans can tolerate some variation in humidity, and a relative humidity (RH) from 20% - 60% will in normal conditions have little influence on the experienced indoor climate. The recommended relative humidity changes with the outdoor temperature. When the outdoor temperature is low, an acceptable indoor RH could be 20% - 40%, since the low air humidity reduces the risk of condensation. *Becher, Bjerke, Martinsen, & Øvrevik* (2016), *Helsedirektoratet* (2016).

The concentration of CO_2 has been used as an indicator for bad indoor air quality for more than a century. A high concentration of CO_2 indicates a too low air change in the room, and there may be other pollutions in the air. *European Concerted Action* (1992). The Norwegian institute of public health therefore recommends that the CO_2-concentration should be below 1000 ppm to maintain good indoor air quality *Folkehelseinsituttet* (2015b).

Volatile organic compounds (VOCs) are a combination of different odours and gases that are emitted from toxins and chemicals in everyday products, for example from building materials, maintenance equipment, consumer products, or human breath. Even though only a small amount is emitted from each source, these emitted gases can accumulate over time, and VOCs may cause serious health problems both in the short and long term. *Airthings* (n.d.b). Researchers and indoor environment rating schemes recommend that the amount of VOCs in the indoor air should be below 500 ppb. *WorldGBC* (n.d).

There are many guidelines and recommendations for the different indoor environment parameters, some of them are summed up in Table 1 below.

Table 1:Summary of the recommended values for the indoor environment parameters in Norwegian schools DIBK (2017), Becher, Bjerke, Martinsen, & Øvrevik (2016) Folkehelseinstituttet (2015b), WorldGBC (n.d).

PARAMETER	RECOMMENDED VALUE
TEMPERATURE	Above 19°C Below 22°C
RH	Above 20%
CO_2	Below 1000 ppm
VOC	Below 500 ppb

MACHINE LEARNING

Machine learning (ML) is a subset of Artificial intelligence (AI). The models used in ML are capable of learning from themself. Every time the model runs, it gets a little bit smarter, learning and improving from experience. ML is able to analyse large quantities of data and may deliver more accurate results than other branches within computer science. However, to train the model adequately, more resources and time may be needed. *Expert System Team* (2020).

Building a machine learning model

There are four steps to build a machine learning model. The first one is to select and prepare the training data set. The training data set is data that is representative of the data the model will use to solve its designated problem. The data should be divided into two parts, training and testing. The training part will train the model, while the testing part is used to test and refine the model. The next step is to choose the algorithm that will be used on the training data set. *IBM Cloud Education* (2020).

The third step when building a ML model is to train the algorithm. This is an iterative process; variables are sent through the algorithm, the output is compared with the expected results, and weights and biases in the algorithm can be adjusted based on the accuracy of the output. This trained, accurate algorithm is now the machine learning model. In the last step, the model is used and improved. *IBM Cloud Education* (2020).

Evaluation parameters

While building a machine learning model, it is important to evaluate the model. In a classification problem, there are generally four different outcomes: True positives, true negatives, false positives or false negatives. It is possible to use these four outcomes to evaluate the model. The true values are the values where the model have predicted correctly, while the false values are where the model have predicted incorrectly. *Jordan* (2017).

The accuracy of the model is the percentage of correct predictions for the test data and can be calculated with equation (1). *Jordan* (2017).

$$accuracy = \frac{true\ positives + true\ negatives}{all\ predictions} \tag{1}$$

Precision is the fraction of the correct predictions among the examples that were predicted to belong in the class, as shown in equation (2). On the other hand, the recall is the fraction of relevant examples that were predicted to be in a class with respect to the examples that actually belong in the class. This is shown in equation (3). Another name for recall is the true positive rate. *Jordan* (2017).

$$precision = \frac{true\ positives}{true\ positives + false\ positives} \tag{2}$$

$$recall = \frac{true\ positives}{true\ positives + false\ negatives} \tag{3}$$

It is also possible to look at the false positive rate, shown in equation (4), which is the proportion of negative data that is mistakenly considered positive. *Mishra* (2018).

$$false\ positive\ rate = \frac{false\ positives}{true\ negatives + false\ positives} \tag{4}$$

When the classes are unevenly distributed, these evaluation methods may not be very useful. If only 1% are in one of the classes, and 99% in the other, it would be easy to just build a classifier that always predicts the second class. *Jordan* (2017).

A way to inspect the model when the classes are uneven is by using the F-measure. The F-measure combines the precision and the recall, as shown in equation (5). The higher F-measure, the better the performance of the model. *Jordan* (2017).

$$\text{F-}measure = \frac{2 \cdot precision \cdot recall}{precision + recall} \tag{5}$$

When dealing with a binary classification problem, the true positive rate and the false positive rate is often plotted in a graph, in order to evaluate the area under the curve (AUC). This is called the receiver operating characteristic (ROC) curve. A model with high AUC is better for predicting true positives and true negatives than a model with low AUC. *Manna* (2020).

Library

In this project two different algorithms are used. The first one is XGBoost, which stands for eXtreme Gradient Boosting. This algorithm is often used within supervised learning. It is based on decision threes and uses a gradient boosting framework. It is possible to use the in-built XGBClassifier on classification problems such as the one that appears in this project. *Brownlee* (2016).

The second algorithm used, also used for gradient boosting on decision trees, is CatBoost. It is a readymade classifier that works well with different types of data and provides state of the art results. The name is a combination of the words “Category” and “Boosting”. It is possible to use the CatBoostClassifier that trains and applies models with a classification problem. *Banerjee* (2020).

METHODOLOGY

Three different methods were used to investigate the indoor environment and pupils’ health in different schools. In this article, the results from one of the schools is presented. The chosen school is a lower secondary school in Oslo, built in 1972.

The ventilation and heating system was upgraded in 2005, and there are approximately 600 pupils. The heating system is controlled by the outside temperature, and thus it will vary with the outdoor temperature due to a pre-set form which is the basis for how much heat should be delivered to the rooms. The ventilation air flow is managed by Undervisningsbygg Oslo and is set with a temperature of 19°C for the classrooms.

Field measurements were carried out in ten classrooms. The pupils in the school were given a survey from NAAF called “Mitt Inneklima”, and these results were implemented in a ML model. The goal was to find connections between different health problems and the experienced indoor environment.

Field measurements

For field measurements, the equipment used was Airhtings Wave Plus sensors and Airthings Hub as shown in Figure 1. Airthings Wave Plus is a wireless Radon and Indoor Air Quality Monitor. A local hub collects the signals from the instruments in the different rooms, allowing remote access to all the results from their website.

The parameters measured by Airthings Wave Plus are radon, airborne chemicals (VOCs), CO_2, relative humidity, temperature, and air pressure. The sampling interval is five minutes. The sensor specifications are shown in Table 2. The accuracy for CO_2 is the highest value between 30 ppm and 3%. This means that the accuracy is ± 30 ppm with a CO_2-concentration below 1000 ppm, while it is ± 3% of the value when the concentration is higher than 1000 ppm. *Airthings* (n.d.a), *Airthings* (n.d.d).

Figure 1: Airthings Wave Plus (left) and Hub (Right). Airthings (n.d.c), Airthings(n.d.a).

Table 2: Sensor specifications for Airthings Wave Plus. Airthings (n.d.d).

SENSOR SPECIFICATIONS

TEMPERATURE	Range	4°C – 40°C
	Accuracy	± 0.1°C
	Resolution	0.01°C
RH	Range	0% – 85%
	Accuracy	± 1%
	Resolution	0.5%
CO_2	Range	400 – 5000 ppm
	Accuracy	± 30 ppm or ± 3%
	Resolution	1 ppm
VOC	Range	0 – 10 000 ppb
	Accuracy	-
	Resolution	1 ppb

The parameters that were investigated was temperature, relative humidity, CO_2-concentration, and VOCs. The results used in this article was measured in the period between 16.11.20 – 27.11.20.

Questionnaire design

“Mitt Inneklima” (My Indoor Climate) is a web-based tool from NAAF, which can be used to map how the pupils experience the indoor climate in a school, and whether they have any health problems that may be related to poor indoor climate. The survey is anonymous, and there is no name or other personal characteristics on the questionnaire. This means that no personal data is processed in the survey. *NAAF* (2016).

The results from the survey are given as a percent of how many of the pupils' experience health problems or poor indoor climate every week for the last three months. These results were compared to some reference material. This reference material is based on results from earlier surveys in schools without any known indoor climate problems. The results are shown in two tables, one for the experienced indoor climate, and one for the reported health problems. The result from this survey gives the principal and the school important information in the work with environmental health. *NAAF* (2020).

Machine learning models

By using machine learning, it may be possible to predict whether the pupils will experience health problems when using the known information about the experienced indoor environment. Four machine learning models was developed by a student, Maren Pedersen Feness last spring, and they were made available for use in this project. She also forwarded raw data from earlier surveys on "Mitt Inneklima" in order to train the model to recognize patterns and contexts between experienced indoor environment and different health problems. Results from surveys at the school, as well as the data from Maren, was then processed to make it compliable for use with the machine learning models. Two of the models uses XGBoost and the last two uses CatBoost.

The raw data from the questionnaire needs to be processed because there are several answer choices available. The problem investigated is a classification problem, and thus, the data was reformulated to 0, 1, or "missing" for the answer "I don't know".

In machine learning it is useful to try different methods for solving a problem, and then choose the method that gives the best results. Thus, it is necessary to examine the four different machine learning models after the data is processed, and then decide which of them have the best accuracy. In order to decide which model works the best, it was focused on the values of F-measure and ROC AUC. The F-measure and ROC AUC are combinations of different accuracy-values that are important for finding a good model.

By using the models, the most important features for the different health problems may be found. This is the indoor environment parameters that contributes the most to the different health problems.

RESULTS AND DISCUSSION

Field measurements

The results from the field measurements in two of the classrooms at the school is shown in figure 2 - 5. These graphs show that the temperature is a bit high, the RH is sometimes a bit low, the CO_2-concentration is below the recommended maximum value, while the VOCs have some high peaks. Everyone gets a spray of anti-bac when entering the classroom, which may have influenced the high peaks of VOCs.

During the time when the measurements was taken, the outdoor air was dry and quite cold. In the period with RH below 20% the outdoor temperature was 0°C-5°C and there was no precipitation. The lowest RH for all the classrooms were between 15% and 16% during the measuring period, which is below the recommended values. As a consequence, the pupils may have a feeling of dry skin and mucous membrane.

Generally, these results were representative for all the investigated rooms. Some of the rooms has small periods with slightly too high CO_2-concentration. During the measuring period, the school operated at half capacity due to COVID-19, and the amount of people in the classrooms were halved. This may affect the results, indicating that the results present a much better indoor climate than the normal situation.

It should be noted that the temperature often is higher during the night than during the day. This is because the heating is on around the clock, including during the night and weekends, while the ventilation is only on during the school days.

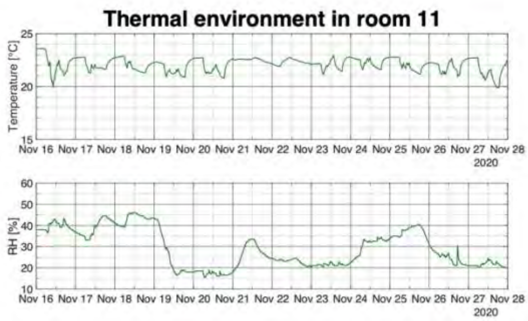

Figure 2: Measured temperature and RH in classroom 11

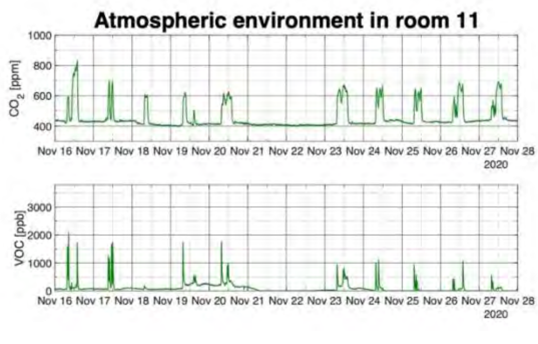

Figure 3: Measured CO_2- and VOC-concentration in classroom 11

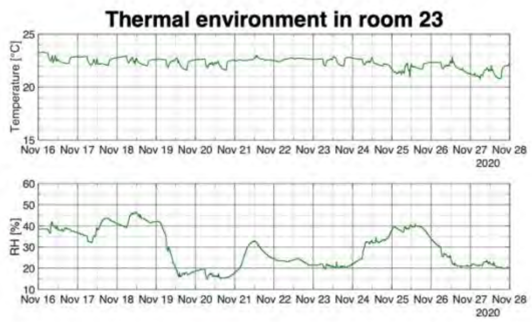

Figure 4: Measured temperature and RH in classroom 23

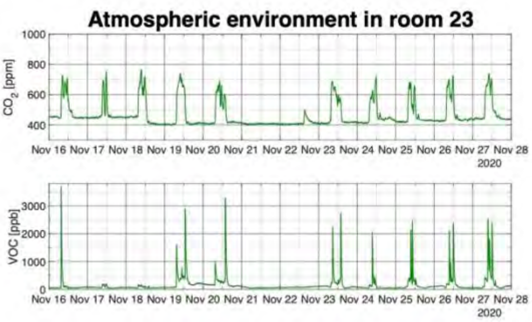

Figure 5: Measured CO_2- and VOC-concentration in classroom 23

Questionnaire

Due to the situation with COVID-19, and other postponements, only 233 pupils at the school had completed the survey when the data was forwarded. This is a relatively small part of the pupils (38.6%), so the result might not be representative for the whole school. The next two tables were compiled with the results from the survey. As shown in Table 3, more of the pupils are experiencing different indoor climate problems every week compared to the reference school for almost all the parameters. The last three parameters do not have reference values yet and are thus not compared.

Four of the parameters are within or below the uncertainty of the reference school. Those are the parameters shown in green in Table 3. The only parameter that is below the uncertainty of the reference school is that it is difficult to hear when other people talk in the classroom. This means that the pupils at this school do not have problems with hearing their teacher.

From this, it is possible to conclude that generally, the pupils experience a worse indoor climate than the reference school. 52% of the pupils' experience that it is too hot every week, while 71% thinks there is poor indoor air, indicating a suboptimal learning environment.

Table 3: Reported indoor climate problems every week, compared to the reference values with the given uncertainties

EXPERIENCED INDOOR CLIMATE	RESULT	REFERENCE
DRAUGHT	12%	10% ± 6%
TOO HOT	52%	3% ± 4%
TOO COLD	16%	21% ± 8%
FLUCTUATIONS IN TEMPERATURE	25%	15% ± 6%
POOR IAQ	71%	21% ± 8%
DRY AIR	29%	15% ± 6%
UNPLEASANT SMELL	18%	8% ± 5%
STATIC ELECTRICITY	3%	6% ± 5%
DIFFICULT TO HEAR OTHER PEOPLE TALKING	5%	17% ± 8%
NOISE FROM OTHER PUPILS	23%	10% ± 6%
NOISE FROM OUTSIDE	18%	8% ± 6%
NOISE FROM ELECTRICAL OR OTHER EQUIPMENT	23%	8% ± 6%
DUST AND DIRT	23%	8% ± 6%
POOR LIGHT	7%	-
UNPLEASANT LIGHT	14%	-
UNPLEASANT SUNLIGHT	6%	-

From Table 4, it is found that every health problem is experienced by more pupils more often than in the reference school. 58% of the pupils' experience fatigue every week, which is over half of them. 34% of the pupils at the school experience concentration problems while 33% of the pupils are feeling heavy-headed every week. These results show that the pupils are affected by the indoor environment. A high temperature may contribute to the feeling of fatigue and concentration problems, while poor IAQ may contribute to the concentration problems as well as the feeling of being heavy headed.

Table 4: Reported health problems every week, compared to the reference values with the given uncertainties.

HEALTH PROBLEMS	RESULT	REFERENCE
FATIGUE	58%	28% ± 8%
HEADACHE	22%	14% ± 6%
FEELING HEAVY-HEADED	34%	9% ± 6%
DIZZINESS	18%	3% ± 4%
CONCENTRATION PROBLEM	33%	13% ± 6%
EYE IRRITATION	17%	5% ± 5%
IRRITATED NOSE	13%	7% ± 5%
HOARSENESS	11%	5% ± 5%
COUGHING	9%	3% ± 4%
IRRITATED FACIAL SKIN	13%	5% ± 5%
FLAKY/ITCHY SCALP	18%	1% ± 4%
DRY, ITCHY HANDS	15%	2% ± 4%

Machine learning

After the obtained data was processed, the different models were tested. When checking the accuracy for the different models, the main focus was on the F-measure and the ROC AUC. Most of the models had similar values for the accuracy, F-measure and ROC AUC, but the first CatBoost model turned out to be the best model for seven of the twelve health problems. Therefore, it was decided to use this model for all of the health problems.

The features investigated are the different parameters on the experienced indoor climate shown in Table 3, as well as the results from some other questions answered in the survey.

Figure 6 and Figure 7 shows the most important features for the different health problems when using the data from this school. There were only 233 answers from the questionnaire, therefore it might be difficult for the model to find connections between different features and the health problems. For Eye irritation and Coughing, it was found that only three and four features contributed to the problem, respectively.

An important feature for 11 of the 12 health problems is Too hot, the exception being Irritated nose. Dry air is an important feature for nine of the 12 health problems, which is also a large share. The exceptions here are fatigue, dizziness and concentration problems. It is clear that Too hot and Dry air have a negative impact on human health, with one or the other being the most important feature for eight of the 12 health problems.

The five most important features for fatigue are Dust and dirt, Heat from the ovens, Unpleasant light, Noise and Too hot. Heat from the ovens and Too hot may be connected, and it is usual to feel tired if the temperature is high. The fact that unpleasant light and Noise is one of the most important features is also expected, but that Dust and dirt was the most important was unexpected. However, dust and dirt may contribute to poor indoor air quality, which may contribute to fatigue.

An important part of Machine learning is the models' ability to find connections that humans would miss. The results from the ML model shows that there are many connections that makes a lot of sense. However, some of them are not quite as expected. One of them being that Eczema is the most important feature for concentration problems. This may be due to a small data base for the model to use.

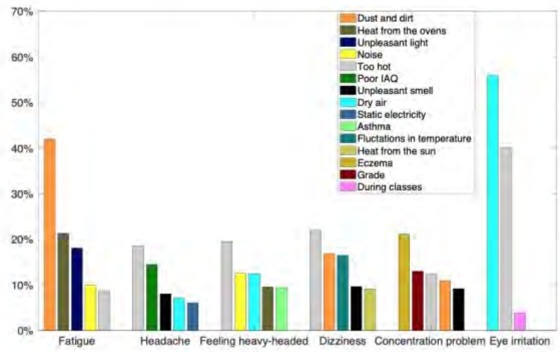

Figure 6: The five most important features for the first six health problems at the school

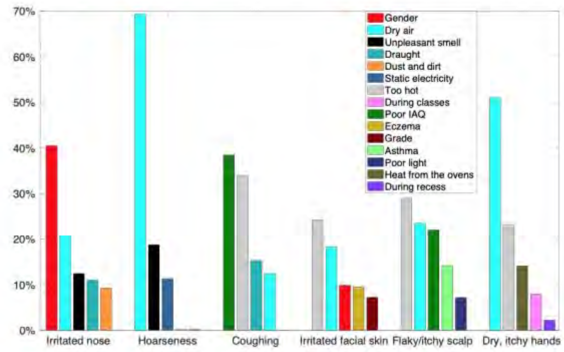

Figure 7: The five most important features for the last six health problems at the school

When using the data from the training set, it was found that Poor IAQ was the most important feature for seven of the 12 health problems, and in top five for two additional ones. This shows that different data gives different results. With data from the school, Poor IAQ was only present as one of the five most important features for three of the health problems.

Dry air, however, was one of the five most important features for seven of the health problems with the data from the training set. This shows that even if there are differences, there are also similarities. The machine learning results from the training set are shown in Figure 8 and Figure 9.

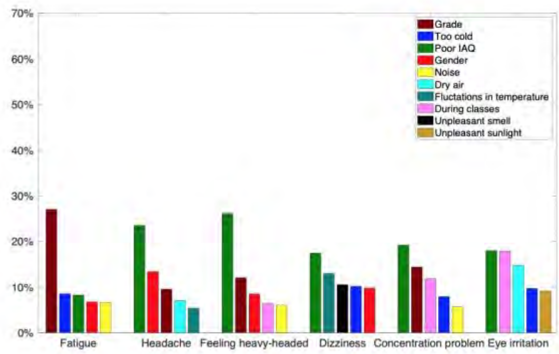

Figure 8: The five most important features for the first six health problems with data from the training set

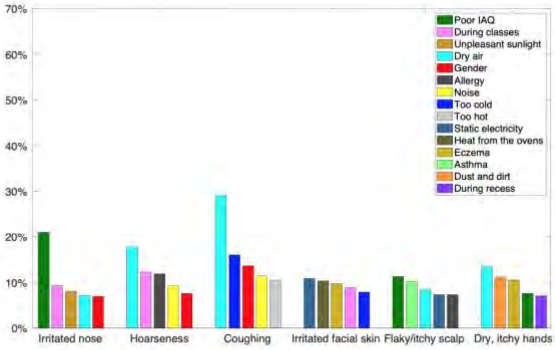

Figure 9: The five most important features for the last six health problems with data from the training set

DISCUSSION

Is there a correlation between the survey, the measurements and the results from the machine learning model? Results from the field measurements shows that the temperature in the classrooms is too high, while the relative humidity sometimes is too low. This agrees with both the results from the questionnaire and the results from the machine learning. According to the questionnaire, 52% of the pupils' experience that the indoor environment is too hot every week. From the machine learning it was found that Too hot is an important feature for 11 of the 12 health problems, while Dry air is an important feature for nine of them.

From this it could be concluded that there should be done some changes to the temperature, and maybe about the humidity in the classrooms. However, it is difficult to make changes to the temperature, since the heating system is controlled by the outdoor temperature. Nevertheless, it might be possible to make some changes and make small adjustments to the set point for the heating. In addition, the heating could be turned down or maybe completely off during the night. It is not necessary to heat the school to above 23°C during the night.

It is difficult to make immediate changes that can affect the low humidity when the outdoor air is dry and cold, but one thing that might work is to change the ventilation system and include a humidifier to increase the humidity in the fresh air. This may be a costly affair, and in addition it might be difficult to control the humidity in the whole building. It is important that the humidity does not increase too much, since it may increase the danger of mould and other micro bacterial growth, as well as moisture damage. Decreasing the temperature and ensuring that the rooms are cleaned thoroughly may lessen the feeling of dry air and might be a better solution than installing a humidifier.

CONCLUSIONS

In this article, the results from investigations at one school in Oslo were presented. The field measurements revealed that the temperature was generally too high, while the humidity was low, and there were some high spikes with VOCs. The CO_2-concentration was typically below 1000 ppm, but due to Corona restrictions the number of pupils in the classrooms were halved during the measuring period. Therefore, the results might indicate a better indoor climate regarding CO_2-concentration than there would be in a normal situation.

The results from the questionnaire shows that more of the investigated pupils have been experiencing different indoor climate problems every week than the reference school. 52% of the pupils' experience that it is too hot every week, while 71% thinks there is a poor IAQ, indicating a suboptimal learning environment. It is also found that every health problem the questionnaire asked about is experienced more often than in the reference school. 58% of the pupils' experience fatigue every week, which is over half of the pupils, while 34% experience concentration problems and 33% are feeling heavy-headed every week.

By using machine learning it is found that Too hot is an important feature for 11 of the 12 health problems, while Dry air is an important feature for nine of the 12 health problems. It is clear that these features have a negative impact on human health, with Too hot or Dry air being the most important feature for eight of the 12 health problems. When looking at the results from the training data set, it was found that Poor IAQ was one of the five most important features for nine of the 12 health problems, while Dry air was one of the most important features for seven of them.

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