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TITLE: Dense Urban Environment Dosimetry for Actionable Information and Recording Exposure (DUE DARE)

PRINCIPAL INVESTIGATOR: Prof. David J. Lary

CONTRACTING ORGANIZATION: University of Texas at Dallas

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In dense urban environments there is currently a lack of accurate actionable information on atmospheric composition (gaseous and particulate) on fine spatial and temporal scales. By simultaneously measuring both the environmental state and the human biometric response we propose a holistic sensing environment and methodology for providing accurate actionable information. A state of the art sensor network involving fixed and mobile sensors using machine learning calibration and uncertainty estimation. Comprehensive wearable biometric sensors are used to characterize the real-time human response to the composition of the air, making the human response an integral part of the sensor network. The holistic sensor network incorporates embedded real time machine learning to increase functionality in providing actionable insights for active human participants.

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1. **INTRODUCTION:** *Narrative that briefly (one paragraph) describes the subject, purpose and scope of the research.*

Our goal is a holistic methodology for providing accurate actionable information on environmental dosimetry for atmospheric composition on fine spatial and temporal scales. The approach uses a state of the art sensor network involving fixed and mobile sensors with real-time cross calibration and uncertainty estimation. Comprehensive wearable biometric sensors are used to characterize the real-time human response to the composition of the air, making the human response an integral part of the sensor network. The holistic sensor network incorporates embedded real time machine learning to increase functionality in providing actionable insights for the active human participants.

2. **KEYWORDS:** *Provide a brief list of keywords (limit to 20 words).*

Dense Urban Environment, Dosimetry, Exposure, Biometrics, Machine Learning

3. **ACCOMPLISHMENTS:** *The PI is reminded that the recipient organization is required to obtain prior written approval from the awarding agency grants official whenever there are significant changes in the project or its direction.*

What were the major goals of the project?

List the major goals of the project as stated in the approved SOW. If the application listed milestones/target dates for important activities or phases of the project, identify these dates and show actual completion dates or the percentage of completion.

- Sensor Acquisition & Calibration: 100% Complete
- Electric Vehicle Environmental Sensor Integration: 100% Complete
- Environmental Measurement Campaigns: 50% Complete
- Low-cost sensor calibration and deployment: 75% Complete
- Publication/Conference Presentation. 1 publication appeared, 3 presentations
- Machine Learning Analysis: 10% Complete
- Survey with participants: 10% Complete
- Machine learning analysis linking biometric responses to environmental triggers: 10% Complete

What was accomplished under these goals?

For this reporting period describe: 1) major activities; 2) specific objectives; 3) significant results or key outcomes, including major findings, developments, or conclusions (both positive and negative); and/or 4) other achievements. Include a discussion of stated goals not met. Description shall include pertinent data and graphs in sufficient detail to explain any significant results achieved. A succinct description of the methodology used shall be provided. As the project progresses to completion, the emphasis in reporting in this section should shift from reporting activities to reporting accomplishments.

- Our first publication using biometrics and machine learning has appeared. The human body exhibits a variety of autonomic responses. For example, changing light intensity provokes a change in the pupil dilation. In the past, formulae for pupil size based on luminance have been derived using traditional empirical approaches. In this paper, we present a different approach to a similar task by using machine learning to examine the multivariate non-linear autonomic response of pupil dilation as a function of a comprehensive suite of more than four hundred environmental parameters leading to the provision of quantitative empirical models. The objectively optimized empirical machine learning models use a multivariate non-linear non-parametric supervised regression algorithm employing an ensemble of regression trees which receive input data from both spectral and biometric data. The models for predicting the participant's pupil diameters from the input data had a fidelity of at least 96.9% for both the training and independent validation data sets. The most important inputs were the light levels (irradiance) of the wavelengths near 562 nm. This coincides with the peak sensitivity of the long-wave photosensitive cones in the retina, which exhibit a maximum absorbance around $\lambda max = 562.8 \pm 4.7$ nm.
- Our environmental surveys of the dense urban environment of the Dallas Fort Worth Metroplex is well underway. We have partnered with local government including Dallas County and the City of Plano.

What opportunities for training and professional development has the project provided?

If the project was not intended to provide training and professional development opportunities or there is nothing significant to report during this reporting period, state "Nothing to Report."

Describe opportunities for training and professional development provided to anyone who worked on the project or anyone who was involved in the activities supported by the project. "Training" activities are those in which individuals with advanced professional skills and experience assist others in attaining greater proficiency. Training activities may include, for example, courses or one-on-one work with a mentor. "Professional development" activities result in increased knowledge or skill in one's area of expertise and may include workshops, conferences, seminars, study groups, and individual study. Include participation in conferences, workshops, and seminars not listed under major activities.

There have been substantial opportunities for training and professional development of the many students involved in this project. This has included 5 high school students, 11 undergraduate students and 5 graduate students. They have been involved in sensor construction, sensor calibration using machine learning, research and analysis, writing research papers, presentations at meetings and to community groups, and significant community outreach.

How were the results disseminated to communities of interest?

If there is nothing significant to report during this reporting period, state "Nothing to Report."

Describe how the results were disseminated to communities of interest. Include any outreach activities that were undertaken to reach members of communities who are not usually aware of these project activities, for the purpose of enhancing public understanding and increasing interest in learning and careers in science, technology, and the humanities.

1. Extended visit to US SOCOM and SOFWERX in Tampa, FL. Presentations to various SOCOM groups. Appointed United States Special Operations Command Fellow, SOFWERX, J5 Futures Missions Directorate. Awarded a numbered acknowledgement coin.
2. Presentation to General Koeniger Commander of the 711th Human Performance Wing. Awarded an acknowledgement coin.
3. Presentation at the Warrior Human Performance Research Center. Awarded an acknowledgement coin.

If this is the final report, state "Nothing to Report."

Describe briefly what you plan to do during the next reporting period to accomplish the goals and objectives.

- Conduct more street level surveys of the dense urban environment.
- Conduct joint comprehensive biometric and environmental measurement campaigns with cyclists.
- Complete deployment 24/7 street level sensors.
- Machine learning analysis of data from comprehensive biometric and environmental measurement campaigns with cyclists.

4. **IMPACT:** D*escribe distinctive contributions, major accomplishments, innovations, successes, or any change in practice or behavior that has come about as a result of the project relative to:*

What was the impact on the development of the principal discipline(s) of the project?
If there is nothing significant to report during this reporting period, state "Nothing to Report."

Describe how findings, results, techniques that were developed or extended, or other products from the project made an impact or are likely to make an impact on the base of knowledge, theory, and research in the principal disciplinary field(s) of the project. Summarize using language that an intelligent lay audience can understand (Scientific American style).

- We have been told by many people in the Human Performance space that this is the first time that such comprehensive environmental and biometric information has been brought together.
- Based on a literature survey, our calibration study of the pupillary response to light provides the most accurate model to date, and the most comprehensive in terms of wavelength resolution.
- Aspects of this study have led to a follow on robotic sentinel team study for SOFWERX answering the question "is the area safe" that uses the same mass spectrometer on a robotic boat.
- Local government in the Dallas area are now partnering with us thanks to the electric survey car that is part of this project.

What was the impact on other disciplines?
If there is nothing significant to report during this reporting period, state "Nothing to Report."

Describe how the findings, results, or techniques that were developed or improved, or other products from the project made an impact or are likely to make an impact on other disciplines.

By definition, this project is multidisciplinary.

- The environmental sensing sentinels deployed as part of this project (electric environmental survey car & 24/7 street level sensors) are benefiting local communities in terms of environmental exposure surveys.
- Local law enforcement with the ability to "sniff" meth houses etc.
- Biometric sensing developed in this project is now being used in a SOCOM POTFF project for "live fire" training at Troysgate.

What was the impact on technology transfer?
If there is nothing significant to report during this reporting period, state "Nothing to Report."

Describe ways in which the project made an impact, or is likely to make an impact, on commercial technology or public use, including:

- *transfer of results to entities in government or industry;*
- *instances where the research has led to the initiation of a start-up company; or*
- *adoption of new practices.*

Nothing to report so far.

What was the impact on society beyond science and technology?
If there is nothing significant to report during this reporting period, state "Nothing to Report."

Describe how results from the project made an impact, or are likely to make an impact, beyond the bounds of science, engineering, and the academic world on areas such as:

- *improving public knowledge, attitudes, skills, and abilities;*
- *changing behavior, practices, decision making, policies (including regulatory policies), or social actions; or*
- *improving social, economic, civic, or environmental conditions.*

- Local government in the Dallas area are now partnering with us thanks to the electric survey car that is part of this project for environmental public health protection. This has led to the city of Plano, TX, requesting us to build them a network of 55 street level 24/7 air quality sentinels of the same kind used in this project to deploy across the city of Plano, TX.
- Dallas county is also now partnering with us and linking our live feed data and maps as part of their environmental health protection.
- Several other "preemptive human protection" projects have been spawned thanks to this study. We greatly appreciate your support, thank you, it is making a difference.
- The community group "Downwinders at Risk," the oldest environmental group in Texas, raised funds and have commissioned us to provide a 11 node network (utilizing the same type of 24/7 sensors as in this study) for one of the most polluted communities in south Dallas.
- Five high school kids have been building the sensors with us, as have 3 undergraduates. A further 11 undergraduate computer science senior design students have been doing a project for a visualization mapping portal, winning First Prize for best senior design project. The undergraduate student who's was involved in designing the long range wireless communication for the street level sentinels won an undergraduate research scholar award for this work. The graduate student who did the work on building the pupil dilation models won a Dean's award for his poster on this work.

5. **CHANGES/PROBLEMS:** *The PD/PI is reminded that the recipient organization is required to obtain prior written approval from the awarding agency grants official whenever there are significant changes in the project or its direction. If not previously reported in writing, provide the following additional information or state, "Nothing to Report," if applicable:*

Nothing to Report

Actual or anticipated problems or delays and actions or plans to resolve them

Describe problems or delays encountered during the reporting period and actions or plans to resolve them.

Nothing to Report

Changes that had a significant impact on expenditures

Describe changes during the reporting period that may have had a significant impact on expenditures, for example, delays in hiring staff or favorable developments that enable meeting objectives at less cost than anticipated.

Nothing to Report

Significant changes in use or care of human subjects, vertebrate animals, biohazards, and/or select agents

Describe significant deviations, unexpected outcomes, or changes in approved protocols for the use or care of human subjects, vertebrate animals, biohazards, and/or select agents during the reporting period. If required, were these changes approved by the applicable institution committee (or equivalent) and reported to the agency? Also specify the applicable Institutional Review Board/ Institutional Animal Care and Use Committee approval dates.

Nothing to Report

Significant changes in use or care of human subjects

Nothing to Report

Significant changes in use or care of vertebrate animals

Not applicable

Significant changes in use of biohazards and/or select agents

Not applicable

6. **PRODUCTS:** *List any products resulting from the project during the reporting period. If there is nothing to report under a particular item, state "Nothing to Report."*

- **Publications, conference papers, and presentations**
  Report only the major publication(s) resulting from the work under this award.

Journal publications. *List peer-reviewed articles or papers appearing in scientific, technical, or professional journals. Identify for each publication: Author(s); title; journal; volume: year; page numbers; status of publication (published; accepted, awaiting publication; submitted, under review; other); acknowledgement of federal support (yes/no).*

Shawhin Talebi, David J Lary, Lakitha OH Wijerante, Tatiana Lary, Modeling Autonomic Pupillary Responses from External Stimuli using Machine Learning, Biomedical Journal of Scientific & Technical Research, 20 (3), 14,999-15,009, (2019)

This award was acknowledged. Thank you!

Books or other non-periodical, one-time publications. *Report any book, monograph, dissertation, abstract, or the like published as or in a separate publication, rather than a periodical or series. Include any significant publication in the proceedings of a one-time conference or in the report of a one-time study, commission, or the like. Identify for each one-time publication: author(s); title; editor; title of collection, if applicable; bibliographic information; year; type of publication (e.g., book, thesis or dissertation); status of publication (published; accepted, awaiting publication; submitted, under review; other); acknowledgement of federal support (yes/no).*

Other publications, conference papers and presentations. *Identify any other publications, conference papers and/or presentations not reported above. Specify the status of the publication as noted above. List presentations made during the last year (international, national, local societies, military meetings, etc.). Use an asterisk (*) if presentation produced a manuscript.*

- **Website(s) or other Internet site(s)**
  List the URL for any Internet site(s) that disseminates the results of the research activities. A short description of each site should be provided. It is not necessary to include the publications already specified above in this section.

- **Technologies or techniques**
  Identify technologies or techniques that resulted from the research activities. Describe the technologies or techniques were shared.

- **Inventions, patent applications, and/or licenses**
  Identify inventions, patent applications with date, and/or licenses that have resulted from the research. Submission of this information as part of an interim research performance progress report is not a substitute for any other invention reporting required under the terms and conditions of an award.

- **Other Products**
  Identify any other reportable outcomes that were developed under this project. Reportable outcomes are defined as a research result that is or relates to a product, scientific advance, or research tool that makes a meaningful contribution toward the understanding, prevention, diagnosis, prognosis, treatment and /or rehabilitation of a disease, injury or condition, or to improve the quality of life. Examples include:
  - *data or databases;*
  - *physical collections;*
  - *audio or video products;*
  - *software;*
  - *models;*
  - *educational aids or curricula;*
  - *instruments or equipment;*
  - *research material (e.g., Germplasm; cell lines, DNA probes, animal models);*
  - *clinical interventions;*
  - *new business creation; and*
  - *other.*

7. PARTICIPANTS & OTHER COLLABORATING ORGANIZATIONS

What individuals have worked on the project?

Provide the following information for: (1) PDs/PIs; and (2) each person who has worked at least one person month per year on the project during the reporting period, regardless of the source of compensation (a person month equals approximately 160 hours of effort). If information is unchanged from a previous submission, provide the name only and indicate "no change".

Example:

Name: *Mary Smith*
Project Role: *Graduate Student*
Researcher Identifier (e.g. ORCID ID): *1234567*
Nearest person month worked: *5*

Contribution to Project: *Ms. Smith has performed work in the area of combined error-control and constrained coding.*
Funding Support: *The Ford Foundation (Complete only if the funding support is provided from other than this award.)*

Shawhin Talebi
Graduate Student
His machine learning research project (part of his graduate study in Physics) led to the publication:

Shawhin Talebi, David J Lary, Lakitha OH Wijerante, Tatiana Lary, Modeling Autonomic Pupillary Responses from External Stimuli using Machine Learning, Biomedical Journal of Scientific & Technical Research, 20 (3), 14,999-15,009, (2019)

Which also won a Dean's award when it was presented as a poster.

Has there been a change in the active other support of the PD/PI(s) or senior/key personnel since the last reporting period?
If there is nothing significant to report during this reporting period, state "Nothing to Report."

If the active support has changed for the PD/PI(s) or senior/key personnel, then describe what the change has been. Changes may occur, for example, if a previously active grant has closed and/or if a previously pending grant is now active. Annotate this information so it is clear what has changed from the previous submission. Submission of other support information is not necessary for pending changes or for changes in the level of effort for active support reported previously. The awarding agency may require prior written approval if a change in active other support significantly impacts the effort on the project that is the subject of the project report.

Nothing to Report

What other organizations were involved as partners?
If there is nothing significant to report during this reporting period, state "Nothing to Report."

Describe partner organizations – academic institutions, other nonprofits, industrial or commercial firms, state or local governments, schools or school systems, or other organizations (foreign or domestic) – that were involved with the project. Partner organizations may have provided financial or in-kind support, supplied facilities or equipment, collaborated in the research, exchanged personnel, or otherwise contributed.

Provide the following information for each partnership:
Organization Name:
Location of Organization: (if foreign location list country)
Partner's contribution to the project (identify one or more)
- *Financial support;*
- *In-kind support (e.g., partner makes software, computers, equipment, etc., available to project staff);*
- *Facilities (e.g., project staff use the partner's facilities for project activities);*
- *Collaboration (e.g., partner's staff work with project staff on the project);*

- *Personnel exchanges (e.g., project staff and/or partner's staff use each other's facilities, work at each other's site); and*

Prof. Guido Verbeck's group at the University of North Texas built for us the mass spectrometer. One of only ten of its kind in the world which has performed better than the reference instruments at the Army proving ground trials in 2019. We gratefully acknowledge and appreciate their partnership.

8. SPECIAL REPORTING REQUIREMENTS

COLLABORATIVE AWARDS: *For collaborative awards, independent reports are required from BOTH the Initiating Principal Investigator (PI) and the Collaborating/Partnering PI. A duplicative report is acceptable; however, tasks shall be clearly marked with the responsible PI and research site. A report shall be submitted to* ***https://ers.amedd.army.mil*** *for each unique award.*

QUAD CHARTS: *If applicable, the Quad Chart (available on https://www.usamraa.army.mil) should be updated and submitted with attachments.*

Dense Urban Environment Dosimetry for Actionable Information and Recording Exposure (DUE DARE)

BA170483

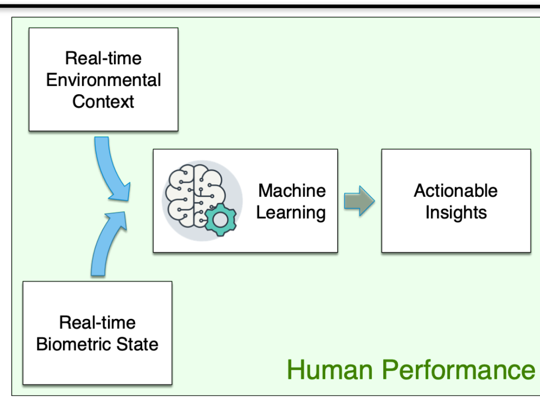
PI: Prof. David J. Lary **Org:** University of Texas at Dallas **Award Amount:** $558,235

Study Aims

In dense urban environments there is currently a lack of accurate actionable information on atmospheric composition (gaseous and particulate) on fine spatial and temporal scales. By simultaneously measuring both the environmental state and the human biometric response we propose a holistic sensing environment and methodology for providing accurate actionable information.

Approach

A state of the art sensor network involving fixed and mobile sensors using machine learning calibration and uncertainty estimation. Comprehensive wearable biometric sensors are used to characterize the real-time human response to the composition of the air, making the human response an integral part of the sensor network. The holistic sensor network incorporates embedded real time machine learning to increase functionality in providing actionable insights for active human participants.



Timeline and Cost

Activities CY	2018	2019	2020
Sensor Acquisition & Calibration – **Milestones**: Low cost sensor calibration/Publication/IRB/HRPO			
Electric Vehicle Integration **Milestones**: Test Survey			
Measurement Campaigns – **Milestones**: Deployment of low cost sensors & Surveys			
Machine Learning Analysis – **Milestones**: Publication/Final Report/Fort Detrick presentation			
Estimated Budget **Updated:** UT Dallas, Jan 17, 2019	$200k	$300k	balance

Goals/Milestones

CY18 Goals – Sensor Acquisition & Calibration
- Sensor acquisition

CY19 Goals – Electric Vehicle Integration & Measurement Campaigns
- Low-cost sensor calibration and deployment
- Vehicle sensor suite training
- Vehicle sensor suite testing
- Publication/Conference Presentation
- Integration of vehicle sensors into sensor pod
- Integration of sensor pod into car

CY20 Goal – Machine Learning Analysis
- Survey with participants
- Machine learning analysis linking biometric responses to environmental triggers

9. **APPENDICES:** *Attach all appendices that contain information that supplements, clarifies or supports the text. Examples include original copies of journal articles, reprints of manuscripts and abstracts, a curriculum vitae, patent applications, study questionnaires, and surveys, etc.*

Research Article

BIOMEDICAL
Journal of Scientific & Technical Research

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Modeling Autonomic Pupillary Responses from External Stimuli using Machine Learning

Shawhin Talebi*, David J Lary, Lakitha OH Wijerante and Tatiana Lary

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ABSTRACT

The human body exhibits a variety of autonomic responses. For ex-ample, changing light intensity provokes a change in the pupil dilation. In the past, formulae for pupil size based on luminance have been de-rived using traditional empirical approaches. In this paper, we present a different approach to a similar task by using machine learning to ex-amine the multivariate non-linear autonomic response of pupil dilation as a function of a comprehensive suite of more than four hundred environmental parameters leading to the provision of quantitative empirical models. The objectively optimized empirical machine learning models use a multivariate non-linear non-parametric supervised regression algorithm employing an ensemble of regression trees which receive input data from both spectral and biometric data. The models for predicting the participant's pupil diameters from the input data had a delity of at least 96.9% for both the training and independent validation data sets. The most important inputs were the light levels (illuminance) of the wavelengths near 562 nm. This coincides with the peak sensitivity of the longwave photosensitive cones in the retina, which exhibit a maximum absorbance around max = 562.8 4.7 nm.

Introduction

This study is part of a broader investigation into the role of the environment in influencing human physical and cognitive performance. The main purpose of this paper is to provide a baseline which accurately describes how changing illuminace a ects pupil dilation, so that when emotional or cognitive factors are also involved, we can start to discern the relative roles of illumnance and cognitive load in a ecting the pupil dilation [1-3]. The ranking of the importance of the predictor variables used in our empirical machine learning models provides a useful metric of which variables are the key drivers, providing us with valuable insights. The Autonomic Nervous System (ANT) is responsible for changes in pupil dilation. The changes in pupil dilation may occur due to changing light intensity, cognitive load and emotional load [4]. While the light intensity allows an immediate response at the retinal level, an emotional and especially cognitive response, require some higher level processing. So, when the visual input is sent from the eye to the visual cortex via the optic nerve, it rst goes through the thalamus. If at this point an imminent threat is detected, it responds mobilizing the body for a ` ght or ight' response, which is then re ected in the changes in the pupil size. As the visual information is relayed to the visual center of the brain in the occipital lobe, it is further sent for processing via various routes to different parts of the brain. In a fast paced changing environment, executive function in the prefrontal lobes make decisions in a fraction of a second. This process also e ects changes in pupil dilation. Some areas of the brain involved in the processing of cognitive and emotional load are deep seated structures and can only be observed by expensive equipment such as fMRI in an artificial lab setting. So, part of the question we are starting to address in this study is how can we tell the difference to which stimuli the pupil is responding? This study begins to answer this question using non-invasive methods that can be used in a natural setting by providing a methodology to accurately model the change in pupil size as a function of key environmental variables, so that when other changes are also occurring simultaneously (such as emotional and cognitive load) we can start to examine how these factors modify the pupil dilation response that occurs.

In addition to changes in pupil dilation, other autonomic responses include changes in heart rate variability, galvanic skin response (or sweating), and core temperature [5-7]. Each of these responses are influenced by variables such as cognitive load [8-11], age [12], pain level [13], and emotional state [14]. In several previous studies formulae for pupil size utilized a single variable, luminance [15-19]. A major shortcoming of these models is their lack of generality. This is illustrated in Figure 1, where the true pupil diameter is plotted against the estimated pupil diameter provided by each of the models enumerated in the legend. There is a clear contrast between the di use cloud of data points from previous model predictions and the high delity predictions of the machine learning model developed here, shown by the green (training points) and the red (independent validation points) in the foreground. Of the ve previous models, Holladay's formula [15] performed the best, with a delity of 25%. The substantial error of these previous models is a likely re ection of both missing parameters being missing and the challenge of ending the exact functional form required for predicting the pupil diameter. Later models added variables such as adaptation eld, age, and monocular adaptation [2,16-21]. All of the earlier models considered ambient light levels by way of the total luminance as opposed to the ne wavelength resolution of the UV/visible spectrum that was used in this study. The ne wavelength resolution allows one to identify the wavelengths to which the pupil dilation is most sensitive, it is noteworthy that there are some small variations from eye to eye in the key wavelengths for determining the pupil diameter. In this study we have utilized recent technological developments, the full visible spectrum and pupil size can be measured with high accuracy and in large volume combined with machine learning, this provides new opportunities for the development of much more robust higher delity empirical models.

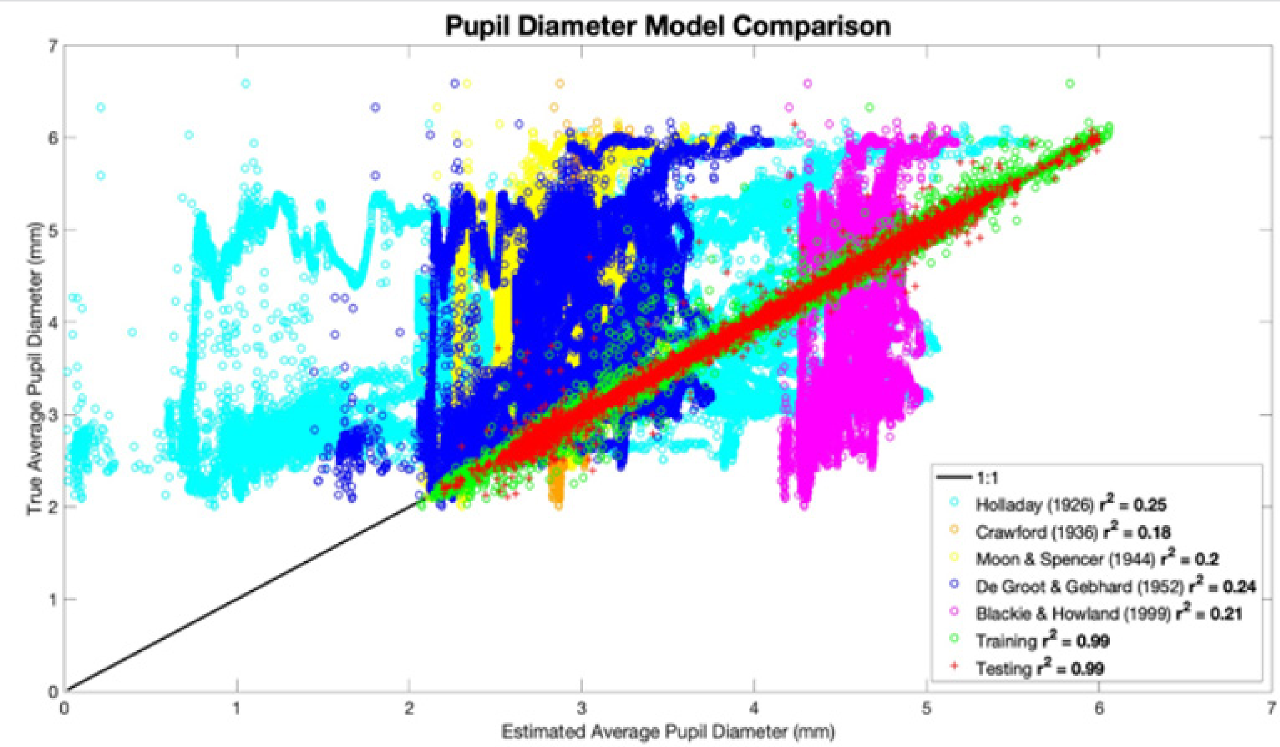

Figure 1: Evaluation and comparison of previous pupil diameter models which utilized a single variable, luminance, showing poor fidelity contrasted with the multivariate empirical machine learning model for the average pupil diameter developed in this study showing good fidelity (foreground green training and red validation points). The true average diameter of the left and right pupils is given on the y-axis, and the estimation by each respective model on the x-axis. Luminance was computed from measured illuminance where the luminance was assumed to be isotropic and reflectance assumed to be 1. Models were evaluated based on description by Watson and Yellott [2].

In this rst demonstration case study, with just one participant, we examined the eject of both light intensity and the orientation/motion of the head on the diameter of a participant's pupils. Different illumination environments can be characterized by their spectra. This light consisting of various wavelengths which can interact with different photo-receptors (light sensitive cones) in the retina. This interaction produces electrical signals that are sent to the brain and interpreted as color [22]. These cones are disproportionately sensitive to particular wavelengths with absorbance peaks around 420 nm (violet), 534 nm (green), and 564 nm (yellow-green) [3]. An illustration of these sensitivities can be shown by a plot of the mean absorbance of the three classes of photo-receptors (short-wave, middle-wave, and long-wave cones) vs wavelength (Figure 2).

 DOI: 10.26717/BJSTR.2019.20.003446

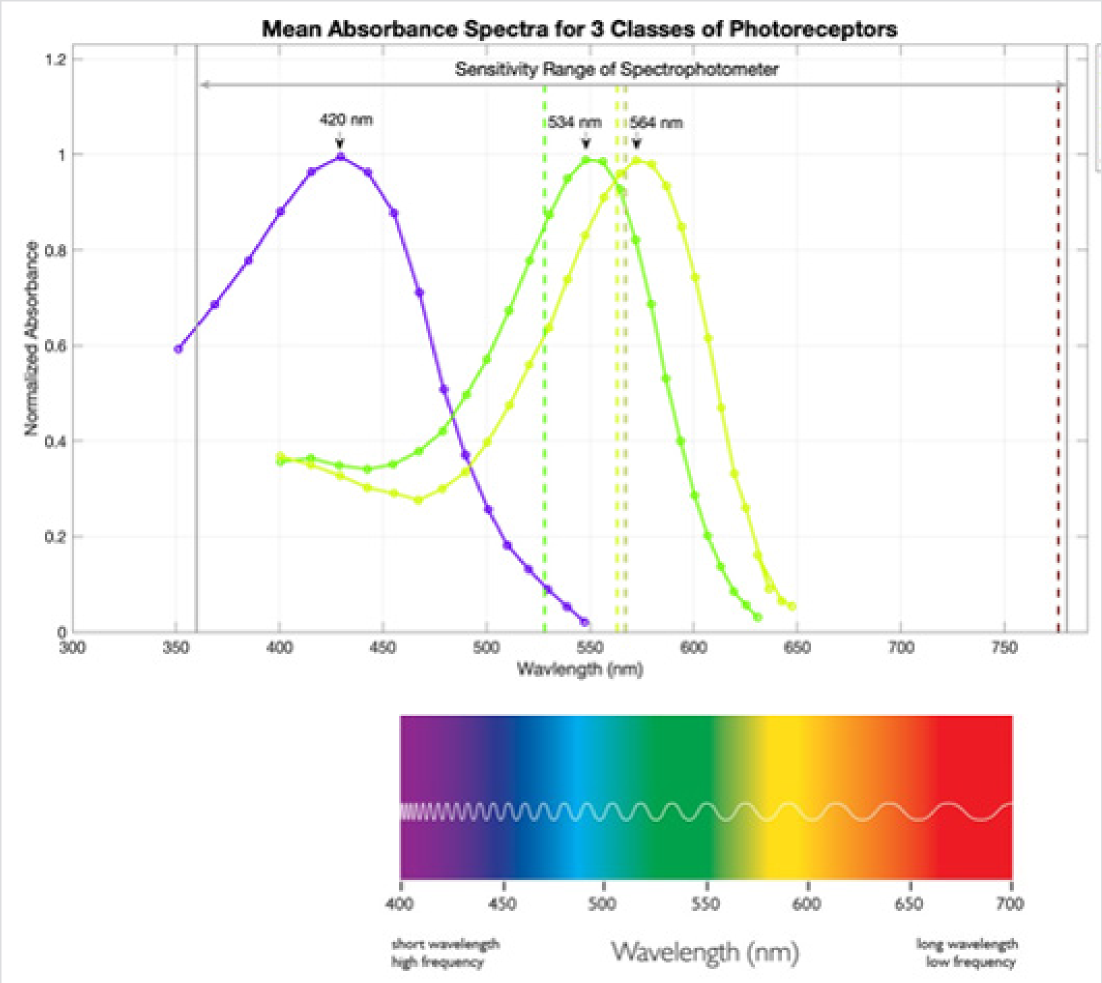

Figure 2: Normalized mean absorbance spectra for long-wave, middle-wave, and short-wave cones. Maximum absorbance values for each class of cones are 420 nm 4.7 nm, 534 nm 3.7 nm, and 564 4.7 nm, respectively. Dashed vertical lines represent the top 4 important predictors taken from the pupil diameter models created here. The sensitivity range of the Konica Minolta CL- 500A Spectrophotometer is 360 – 780 nm indicated by the gray double-sided arrow. Cone absorbances were based on a figure in the paper by Bowmaker and Dartnall [3].

New predictive empirical models of the pupil diameter can be derived using supervised multivariate non-linear non-parametric machine learning regression. The accuracy of the models can be evaluated using an independent validation (or testing) dataset whose data records were not utilized in the model training. This machine learning approach can also provide insights on the relative importance of the inputs (i.e. predictors). In this case we had a few hundred inputs, including the light intensities for every nm of wavelengths from 360-780 nm (ultra-violet to near infrared).

Materials and Methods

Data was collected during 3 outdoor/indoor walks where spectral and biometric data were recorded. The walks took place in the morning (8:30 AM) and late afternoons (4 PM), each lasting approximately fifteen minutes. Spectral data was measured approximately every 3 seconds using a NIST calibrated Konica Minolta CL-500A Illuminance Spectrophotometer, which measures the illumi-nance and spectral irradiance of wavelengths from 360-780 nm with 1 0.3 nm resolution. Pupil diameters, head orientation, and the proper acceleration of the head were recorded 100 times a second using Tobii Pro Glasses 2. The glasses use an infrared grid projected onto each eye to estimate the position and size of the pupils. The orientation and acceleration of the head are estimated using a Microelectromechanical System (MEMS) gyroscope and MEMS accelerometer located in the glasses. Data was prepared and analyzed using Matlab 2019a.

The data preparation involved six steps:

1. **Collection** - Recording of the raw data. Data was written to 6 separate les corresponding to the 2 devices for each of the 3 trials.

2. **Formatting** - Converting raw data les to Matlab timetable objects. 6 timetables were created from the raw data les.

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3. **Synchronizing** - The sampling frequencies differed for each device. 1 record every 3 seconds for the spectral data, versus 100 records every second for the biometric data. To account for this, the 2 timetables for a particular trial were recon gured to share the same time steps using Matlab's retime function with a linear interpolation. The timetables for each trial could then combined using the synchronize function. Resulting in 3 timetables, one for each of the 3 trials.

4. **Merging** - Concatenating all 3 timetables into a single timetable.

5. **Cleaning** - Removing records with device error ags, NaN elements, and zero values for pupil diameter. The latter case is addressed below.

6. **Generating** - Creating new variables such as the average pupil diameter and inter-eye pupil diameter difference.

A major challenge was introduced in step 5 (cleaning) of the data preparation due to a significant portion of the pupil diameter records taking values of 0. This was a non-physical consequence of the mechanism with which the pupil diameters were measured. When there is a high intensity of ambient infrared light from bright sunshine the glasses can no longer readily discern the pupil diameter, this is re ected in Figure 3 where pupil diameter dropouts coincide with time intervals of high spectral irradiance. These records were removed from the data, reducing the number of records from 380,000 to 80,000 records.

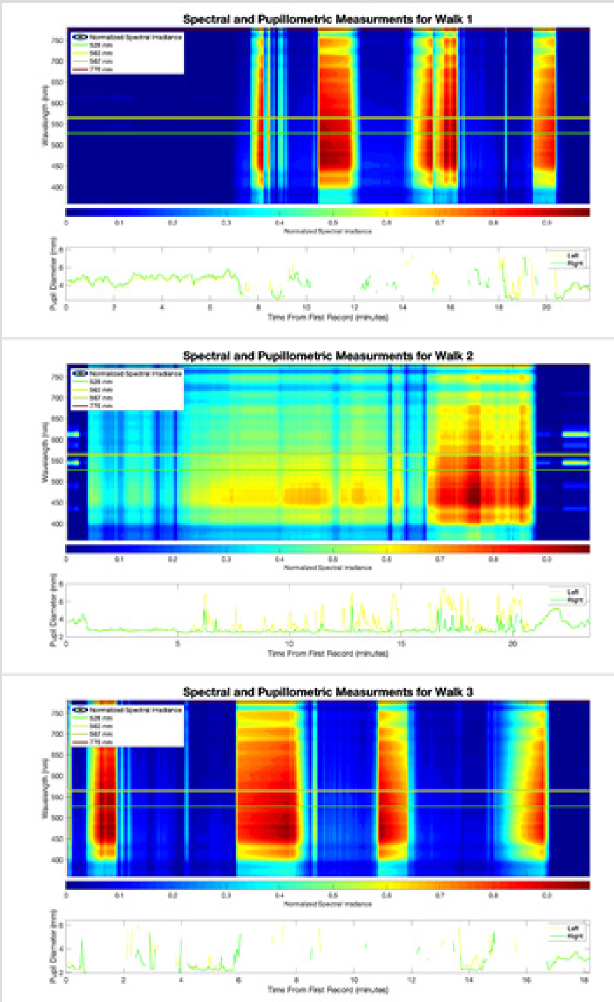

Figure 3: The normalized spectral irradiance at every time step for all walks is plotted. The irradiance is normalized by dividing all values by the maximum spectral irradiance within each walk. Relative size of irradiance values are in- dicated by the colorbar. Spectral lines at 528, 563, 567, and 776 nm represent the most important predictors for the pupil diameter models. Left (yellow) and right (green) pupil diameters are plotted over time. Note the pupil diameter dropouts in time intervals where the spectral irradiance is high.

a) Walk 1

b) measurements during late afternoon (≈ 4 PM).

c) Walk 2 measurements dur- ing morning (≈ 8:30 AM) with overcast.

d) Walk 3 measurements during late afternoon (≈ 4 PM).

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From the recorded data we sought to estimate 5 different parameters, namely the: average of the left and Right Pupil Diameters (APD), Left Pupil Diameter (LPD), Right Pupil Diameter (RPD), magnitude of the difference between the Left and Right Pupil Diameters (PDD), and the illuminance. These parameters can be estimated by constructing objectively optimized empirical machine learning models. The hyperparameters (i.e. the parameters that de ne options associated with the training process) of an ensemble of regression trees able to use both boosting and bagging were optimized (the Matlab function fitrensemble with the Optimize Hyperparameters option set to all). More information on this function is available in the Matlab documentation [23]. We have done many previous machine learning studies [24-56]. The data was split into 2 subsets: one for training and one for the independent testing of each empirical machine learning model. With 90% of the data used for training the multivariate non-linear non-parametric regression models and 10% of the data used for independent testing of the models.

Results and Discussion

In the following subsections we discuss the results of the 5 di erent empirical machine learning models. The accuracy of each model was assessed via a scatter plot of the true vs estimated response variable values (see Figures 4a, 5a, 6a, 7a, & 9a). If the true and estimated values are identical, the resulting scatter plot will be a straight line with a slope of one and an intercept of zero, i.e. a perfect one to one plot with a correlation coe cient, r2, equal to 1. This ideal is indicated by a black line in each scatter plot. The correlation coefficients for the training (plotted as green circles) and testing (plotted as red pluses) datasets were computed using Matlab's corrcoef function.

The relative predictor importance ranking of each model was derived using the predictor Importance function. The relative rankings are visualized as bar plots (see Figures 4b, 5b, 6b, 7b, & 9b). The importance estimates are plotted on a log scale with the most important predictors shown toward the top. In the pupil diameter models (i.e. models for the APD, LPD, RPD, and PDD), the top 20 out of 427 predictors are shown. For the illuminance model, all 7 predictors are given in the ranking. The top 3 predictors are indicated by red bars, the next 2 important predictors by yellow bars, and the remaining predictors by blue bars.

The Average Pupil Diameter Model

Figure 4 shows the results of the Average Pupil Diameter (APD) model. The APD was estimated using the spectral irradiance at every nm between 360-780 nm, the gyroscope, and the accelerometer data as predictor variables. The scatter plot of the true vs the estimated average pupil diameter values is shown in Figure 4a. The model had correlation coefficients of > 0.99 for both the training and testing data subsets. Thus, the empirical machine learning model was successful in predicting the average pupil diameter. Figure 3.1 shows the ranking of the relative importance of the inputs in predicting the APD, the top 3 predictors are the irradiance values at 561, 563, and 562 nm, which coincides with the maximum absorbance of the long-wave cones at around 563 nm [3]. This suggests the long-wave photo-receptors play a more significant role than the short- or middle-wave receptors in controlling the average size of the pupils for the participant.

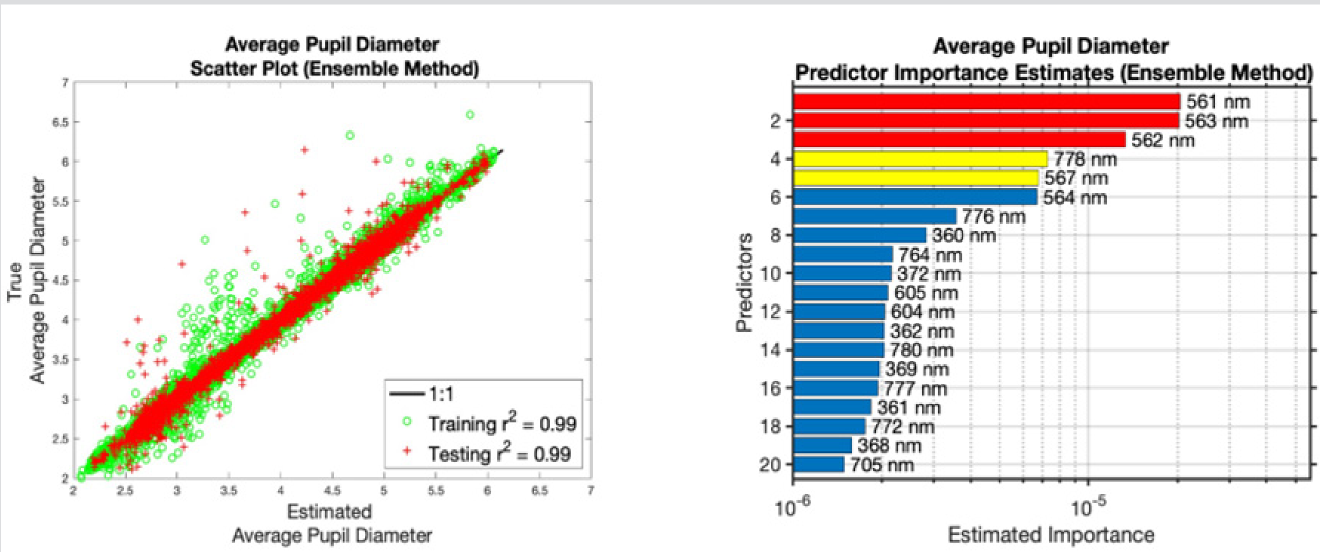

Figure 4: Plots for the average pupil diameter model.

a) True vs estimated average pupil diameter in millimeters.

b) Predictor importance estimates for the average pupil diameter model.

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The Left Pupil Diameter Model

The results for the Left Pupil Diameter (LPD) model are shown in Figure 5. The LPD was estimated using the same predictors as the APD, the spectral irradi-ance from 360-780 nm, the gyroscope, and the accelerometer data. The model was successful in predicting the LPD with a correlation coefficient of > 0.96 for both the training and validation data subsets. The top predictor (567 nm) is again near the maximum absorbance of the long-wave photo-receptors (563 nm). The next top 6 predictors are the irradiance values at 528, 568, 564, 527, 668 and 570 nm, which seem to coincide with both the middle and long-wave photo-receptors with maximum absorbance values near 533.8 3.7 nm and 563 nm, respectively, with the exception of the irradiance at 668 nm [3].

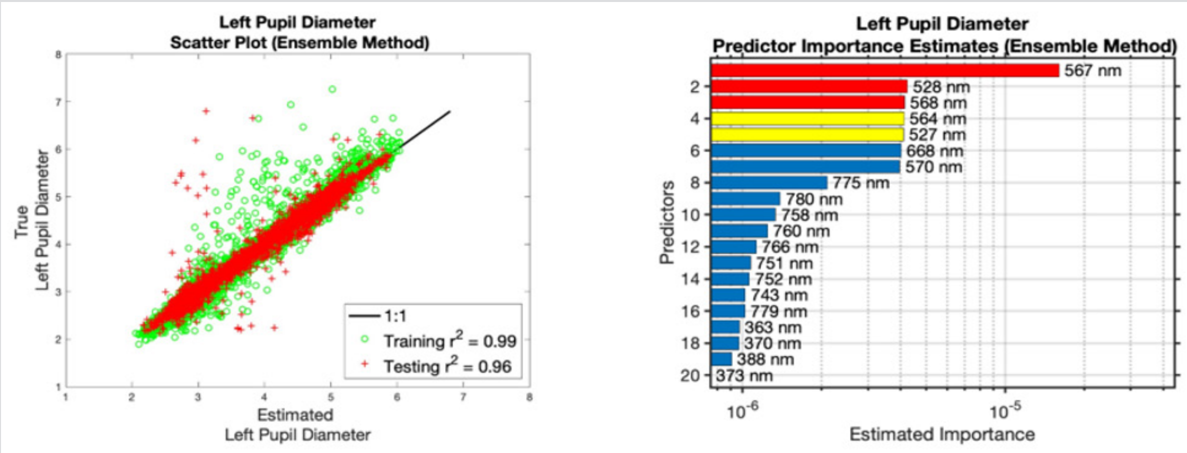

Figure 5: Plots for the left pupil diameter model.

a) True vs estimated left pupil diameter in millimeters.

b) Predictor importance estimates for the left pupil diameter model.

The Right Pupil Diameter Model

The results for the Right Pupil Diameter (RPD) model are shown in Figure 6. The RPD was estimated using the same predictors as the APD and LPD. For the RPD model there is a strong correlation between the estimated and true values, with coefficients of determination > 0.99 for both data subsets, shown in Figure 6a. The top 2 predictors are 563 nm and 562 nm, which again coincide with the maximum absorbance of the long-wave cones near 563 nm. The next most important predictor was the irradiance at 776 nm corresponding to near infrared light. This and the appearance of near infrared predictors in all the importance rankings may be a consequence of the infrared noise in the environment, resulting in the measured pupil diameters to be smaller than the actual values. An interesting result from the importance ranking in Figure 6b, is the appearance of a non-spectral predictor (Accelerometer Z) which denotes the proper acceleration in the direction in front of the glasses. This may be correlated to the participant looking down to navigate obstacles in the walking path such as stairs, inclines, rugged terrain, and other impediments. Focusing on a specific task or object may cause an increase in cognitive load, resulting in a pupillary response [10,11].

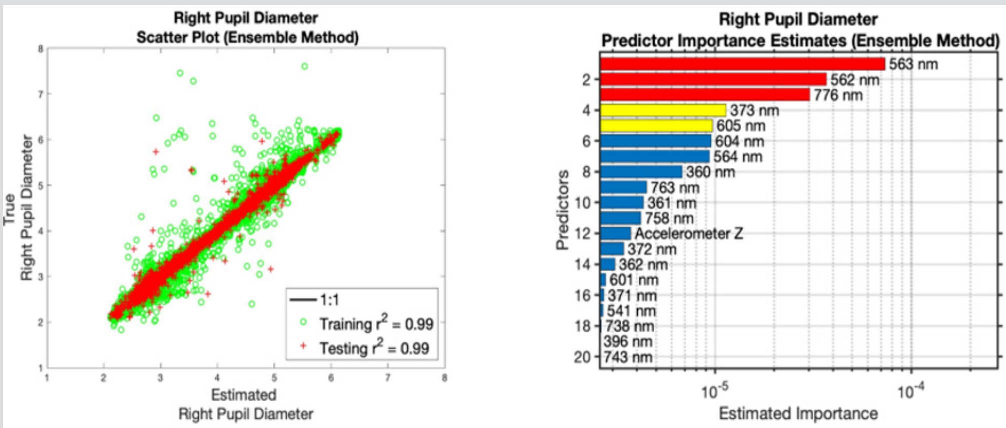

Figure 6: Plots for the right pupil diameter model in millimeters.

a) True vs estimated right pupil diameter.

b) Predictor importance estimates for the right pupil diameter model.

The Pupil Diameter Difference Model and Pupil Asymmetry

The results for the left and right pupil diameter models are noticeably different (see Figures 5 and 6), which may suggest an asymmetry in the behavior of each pupil. One measure of this asymmetry is the magnitude of the difference between the left and right pupil diameters. This is shown by the results of the Pupil Diameter Difference (PDD) model given in Figure 7. The same predictors were used for the PDD model as in the APD, LPD, and RPD models. This empirical model was not successful in predicting the PDD, since the correlation coefficient was 0.43 for the testing data subset, as shown in 3.4. Clearly the most important predictors for modeling this asymmetry were not available in the training dataset.

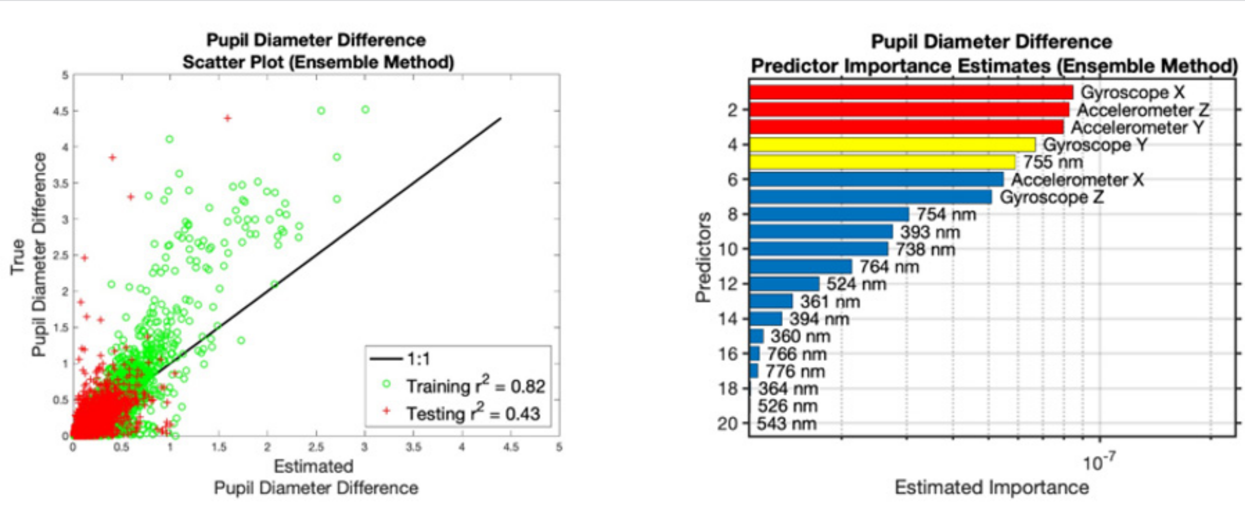

Figure 7: Plots for the pupil diameter difference model.

a) True vs estimated pupil diameter differences in millimeters.

b) Predictor importance estimates for the pupil diameter difference model.

Another metric of the pupil asymmetry can be the accuracy of the LPD model in estimating the RPD and vice versa. The resulting scatter plots are given in Figure 8. Despite the differences in the importance rankings and failures of the PDD model, the estimates are fairly accurate with correlation coefficients of > 0.95 for both the testing and training datasets. This accuracy may suggest that although there is an asymmetry in the importance rankings for the left and right pupil models, the functioning of each pupil is very similar. A possible cause of this asymmetry is ocular dominance (i.e. the input for one eye is preferred over the other) [57,58]. It has been suggested that ocular dominance is not a static phenomenon, but will vary with changing horizontal gaze angle [59].

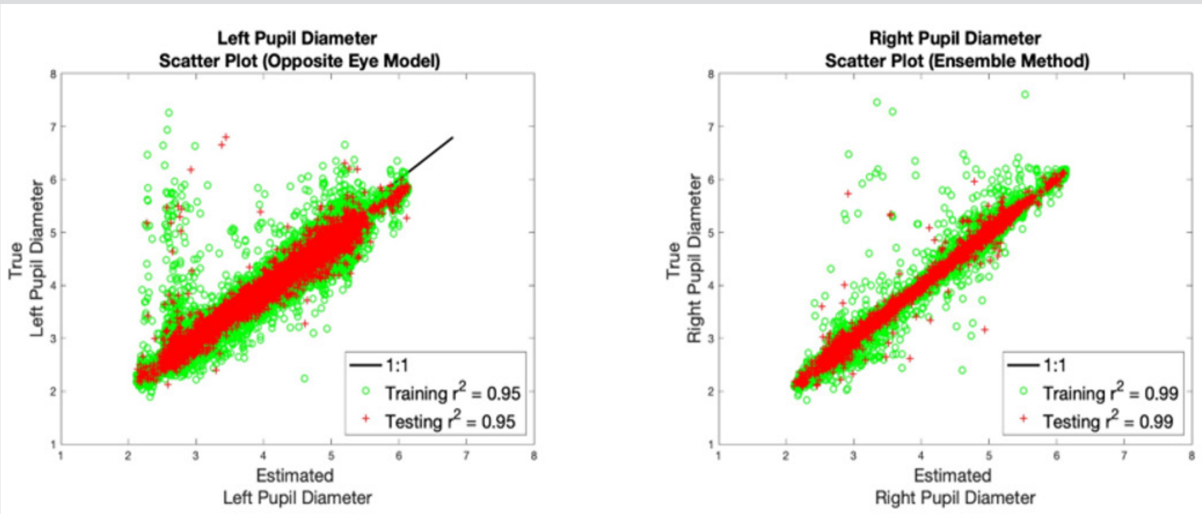

Figure 8: Plots for the pupil diameter prediction using model from opposite eye data. Pupil diameters are in millimeters.

a) True vs estimated left pupil diameter using the right pupil diameter model.

b) True vs estimated right pupil diameter using the left pupil diameter model.

The Illuminance Model

Figure 9 shows the results of the illuminance model. We just saw above that if we know the light intensity we can accurately predict the pupil diameter, so now we `invert' the experiment and ask the question, if we know the pupil diameter can we accurately estimate the light intensity? The model used the pupil diameters, gyroscope, and accelerometer data as the predictors. The estimates were some-what accurate with correlation coefficients of 0.91 and 0.71 for the training and testing datasets, respectively. The top 2 predictors are the left and right pupil diameters, which agrees with rst order considerations of the relationship between pupil diameters and external light levels. The next most important predictor was the acceleration in the z-direction (forward direction). Which may again be correlated with participant focus on obstacle navigation.

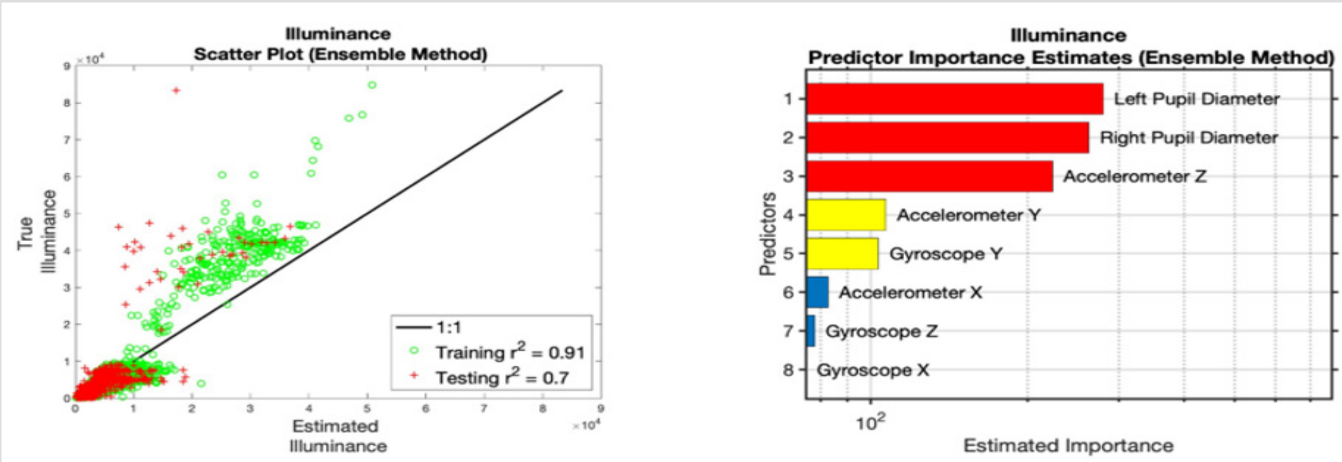

Figure 9: Plots for the illuminance model.

a) True vs estimated illuminance in lux.

b) Predictor importance estimates for the illuminance model.

Pupil Diameter and Illuminance

In a rst order consideration, we can expect the pupil diameter to be inversely proportional to the illuminance. This is depicted in Figure 10, which gives 3 scatter plots of the average, left, and right, pupil diameters vs illuminance. At low illuminance values, the expected inverse relationship is apparent. At higher values (& 4000 lux) this expectation fails. The lack of a clear relationship between the two variables in all situations is likely the main contributor to the failure of previous models (Figure 1).

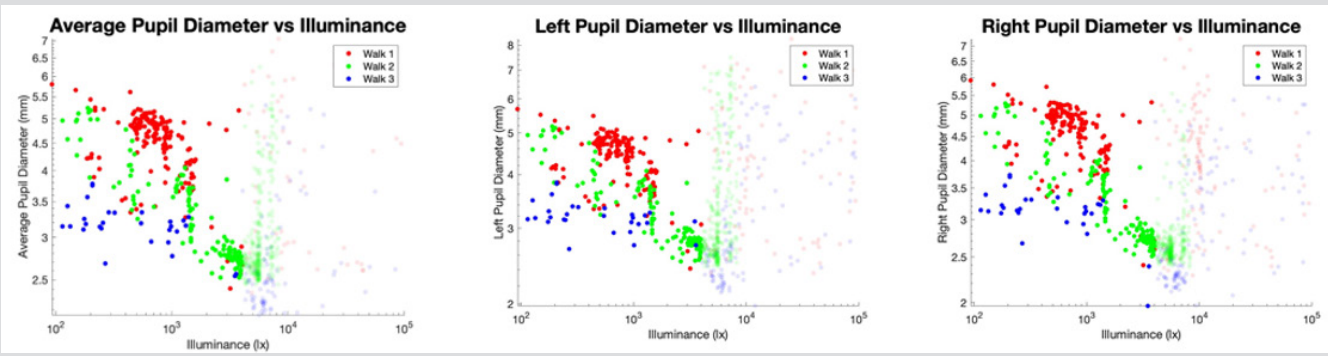

Figure 10: Log scale scatter plots of the pupil diameters vs illuminance. Data from walks 1, 2, and 3 are distinguished by the colors red, green, and blue, respectively. Data points with low opacity have illuminance values above 4000 lx. Note below the 4000 lx mark the variables tend to have an inverse relation- ship.

a) Average pupil diameter vs illuminance.

b) Left pupil diameter vs illuminance.

c) Right pupil diameter vs illuminance.

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The Environment

The normalized spectral irradiance at every time step for each trial is given in Figure 3. Normalized values were computed by dividing all irradiance values by the largest irradiance within each trial. Spectral lines are plotted for 528, 563, 567, and 776 nm, based on the top 3 most important predictors across all pupil diameter models (see Figures 4b, 5b, 6b, & 7b). Where predictors of the spectral irradiance at 561, 562, and 568 nm were disregarded in lieu of the irradiance at 563 and 567 nm.

Temporal discontinuities in the spectra are due to those time intervals in which the participant walked in and out of shaded areas and/or away from the sun, which resulted in orders of magnitude differences in the spectral irradiance. Figure 11 depicts the normalized spectral irradiance plotted on a log scale. Time intervals colored predominately red represent outdoor spectra, while more colorful intervals are indoor.

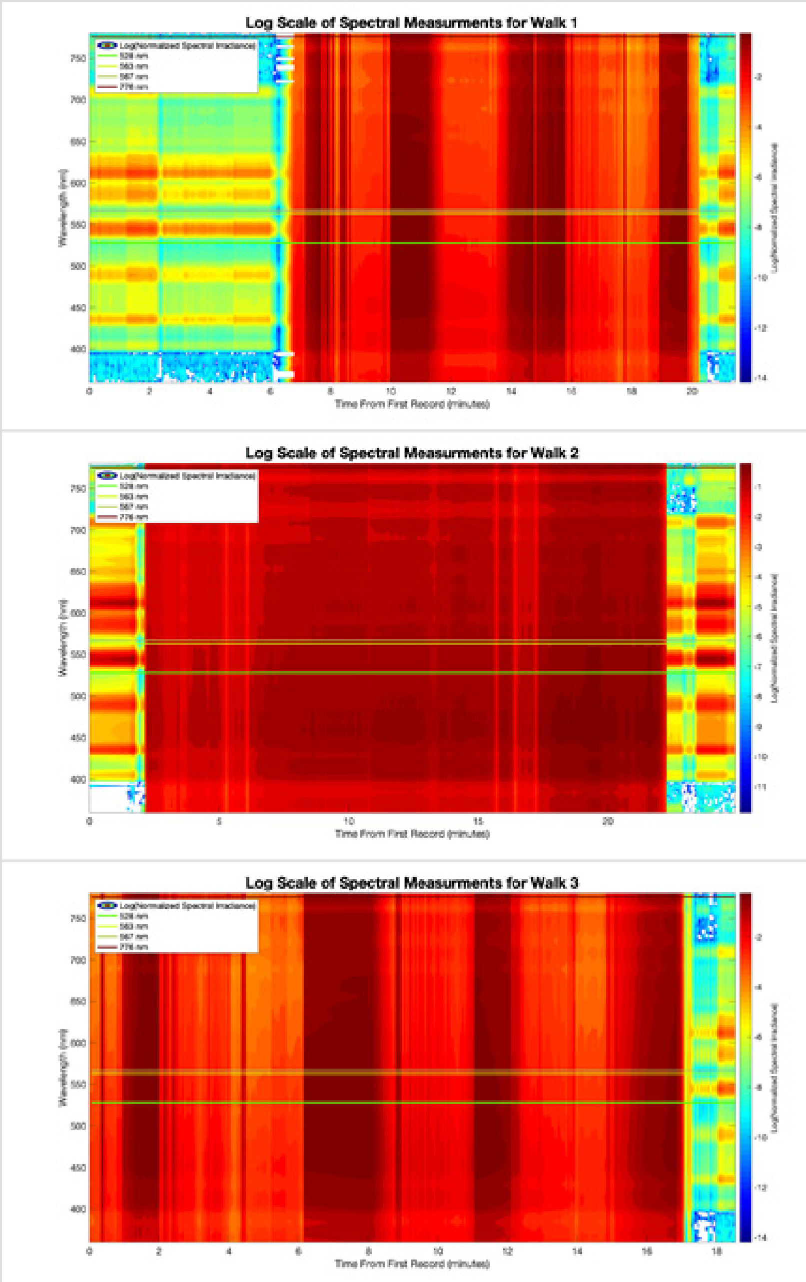

Figure 11: The log of the normalized spectral irradiance at every time step for all walks is plotted. The irradiance is normalized prior to taking log by dividing all values by the maximum spectral irradiance within each walk. Relative sizes of irradiance values are indicated by the color bar. Spectral lines at 528, 563, 13, 567, and 776 nm represent wavelengths of the most important predictors for the pupil diameter models.

a) Walk 1 measurements during late afternoon (≈ 4PM).

b) Walk 2 measurements during morning (≈ 8:30 AM). c)

(c) Walk 3 measurements during late afternoon (≈ 4PM).

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Limitations

The high level of infrared noise caused significant drawbacks in the data analysis. Further developments may require light intensities and spectra to be within a non-disruptive range. Another solution may be to utilize an eye tracking instrument which uses visible light to estimate the pupil diameters.

Future Directions

Pupil size along with other autonomic responses such as heart rate variability, galvanic skin response, and core temperature changes have been associated with cognitive load and performance [5-11]. Although cognitive load is a significant contributor to the provocation of these responses, in a dynamic outdoor environment and while performing a physical activity (such as walking or cycling) it is not always clear which responses were due to external stimuli or cognitive status. Using a similar approach to the one used here, future data collection will expand the number of participants, environments, cognitive tasks, and biometric sensors.

Looking forward, multiple participants will allow for the assessment of the inter-person variability of the models, including parameters such as age and body composition. Different environments will vary in light intensity, air qual-ity, elevation, and temperature. Environmental variables can be measured using mobile weather stations mounted on a participant or bicycle. Other environmental sensors such as a video camera, microphone, and LIDAR can indicate dynamic eld situations and track events. Tasks such as walking, and cycling will be per-formed. Cyclist performance can be assessed via bicycle speed and biometric data. Biometrics such as Electroencephalography (EEG), Heart Rate (ECG), Gal-Vanic Skin Response (GSR), body temperature, Electromyography (EMG), blood oxygen level, and respiration will be considered and modeled. The ranking of predictor importance for these biometric models can help identify important relationships between environmental stimuli and different autonomic response.

Conclusion

Past formulae for predicting pupil diameter mainly considered total ambient light levels via luminance [2,15-21], these models could not capture the fully multi-variate and non-linear dependence of pupil diameter on the environmental state, and consequently had poor generalization. When considering the spectrum of light from 360-780 nm (ultra-violet to near infrared) in lieu of the luminance, we were able to derive a very accurate empirical machine learning model which can predict pupil diameters with a minimum delity of 96.9%. The machine learning also allowed us to identify that the most important wavelengths in predicting the pupil diameters were around 562 nm (green), which is near the peak absorbance of the long-wave photo-receptive cones (562.8 4.7 nm) [3].

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