Enhancing prenatal care through deep learning

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Summary

In this thesis, we aimed to address the challenges in improving prenatal care through the development and evaluation of deep learning algorithms. Our focus was on enhancing the accuracy and precision of fetal ultrasound biometry, fetal birth weight estimation, and computer-assisted surgery, particularly for Twin-to-Twin Transfusion Syndrome fetoscopic laser photocoagulation. Our study aimed to demonstrate the effectiveness of deep learning algorithms in improving prenatal care, with the ultimate goal of reducing adverse outcomes and improving the quality of care for pregnant women and their babies.

In **Chapter 2**, we presented a method for fetal ultrasound video scan analysis and interpretation. Our method simultaneously localized standard planes in video sequences, classified and measured fetal biometric parameters, and estimated gestational age and fetal weight. We demonstrated that our method achieved human-level performance, comparable to inter-rater agreement, including experienced sonographers. Our method has the potential for use as a fetal biometry assistance tool that may save time when reading fetal ultrasounds.

In **Chapter 3**, we presented an end-to-end method that automatically performed fetal birth weight prediction on fetal ultrasound video scans acquired less than 24 hours before delivery without the need for finding standard planes. Our method has the potential to help clinicians select the safest type of delivery for the mother and the child.

In **Chapter 4**, we presented a method for fetal birth weight prediction using fetal multimodal data, an extension of **Chapter 3**. We used fetal ultrasound videos and clinical (tabular) data to develop a custom Transformer module that can efficiently embed clinical data into an image feature representation. Our experiments showed that our method outperformed existing state-of-the-art algorithm approaches and expert clinicians who applied available commercial tools. Furthermore, the use of standalone abdominal video

scans resulted in fetal birth weight prediction performance that was within clinical experts' error margins.

In **Chapter 5**, we presented a novel framework and feasibility of using only the fetal abdominal ultrasound video scans and gestational age to estimate fetal weight using a deep learning algorithm. Our experiments showed that abdomen data may be sufficient for this task when artificial intelligence is used.

In **Chapter 6**, we presented a novel framework for real-time placental vessel segmentation in videos obtained during fetoscopic laser photocoagulation for Twin-to-Twin Transfusion Syndrome. We developed custom data augmentations specifically tailored for this task and showed that our method was accurate and robust, with superior performance compared to current state-of-the-art methods.

Finally, in **Chapter 7**, we provided a general discussion of our proposed approaches and findings, including their contributions, limitations, potential clinical applications, and suggestions for future research directions.

Samenvatting

In dit proefschrift beschrijven we oplossingen voor het verbeteren van prenatale zorg door het ontwikkelen en evalueren van deep-learningalgoritmen. Onze focus lag op het verbeteren van de nauwkeurigheid en precisie van foetale echografische biometrie, schatting van foetale geboortegewicht, en computergestuurde chirurgie, met name voor foetoscopische lasercoagulatie bij het tweelingtransfusiesyndroom. Onze studie had als doel om de effectiviteit van deep-learningalgoritmen aan te tonen in de prenatale zorg, daarmee ongunstige uitkomsten te verminderen, en de kwaliteit van de zorg voor zwangere vrouwen en hun baby's te verbeteren.

In **Hoofdstuk 2** presenteren we een methode voor de analyse en interpretatie van foetale echografische videoscans. Onze methode voert de volgende taken tegelijkertijd uit: hij lokaliseert de standaarddoorsneden in videosequenties, meet en classificeert foetale biometrische parameters, en schat de postmenstruele leeftijd en het gewicht van de foetus. We tonen aan dat onze methode een prestatieniveau behaalt, vergelijkbaar met menselijke beoordeling door ervaren echografisten. Onze methode kan in potentieworden gebruikt als hulpmiddel om tijd te besparen bij het beoordelen van foetale echografie.

In **Hoofdstuk 3** presenteren we een end-to-end methode die zonder het lokaliseren van standaardvlakken automatisch voorspellingen doet van het foetale geboortegewicht op echoscans die verkregen zijn binnen 24 uur voor de bevalling. Onze methode kan in potentie clinici helpen bij het kiezen van de veiligste bevallingsmethode voor moeder en kind.

In **Hoofdstuk 4** presenteren we, als uitbreiding van **Hoofdstuk 3**, een methode die het foetale geboortegewicht voorspelt met behulp van multimodale gegevens van de foetus. We gebruiken foetale echografische videos en (tabulaire) klinische gegevens om een aangepaste Transformer-module te ontwikkelen die klinische gegevens efficiënt in een beeldkenmerkrepresentatie kan transformeren. Onze experimenten tonen aan dat onze methode beter

presteert dan bestaande state-of-the-art algoritmen en klinische experts die beschikbare commerciële tools toepassen. Bovendien resulteert het gebruik van abdominale videoscans alleen al in schattingen van het foetale geboortegewicht die binnen de foutmarges van klinische experts vallen.

In **Hoofdstuk 5** presenteren we een nieuw deep-learningframework voor het schatten van het foetale gewicht op basis van alleen foetale abdominale echografie en postmenstruele leeftijd. Onze experimenten tonen aan dat gegevens van alleen de buik mogelijk al voldoende zijn voor deze taak als kunstmatige intelligentie wordt toegepast.

In **Hoofdstuk 6** presenteren we een nieuw framework voor realtime segmentatie van placentavaten in video's verkregen tijdens foetoscopische lasercoagulatie voor het tweelingtransfusiesyndroom. We hebben aangepaste data-augmentaties ontwikkeld die specifiek zijn afgestemd op deze taak en hebben aangetoond dat onze methode nauwkeurig en robuust is, met superieure prestaties vergeleken met huidige state-of-the-art-methoden.

Tot slot, in **Hoofdstuk 7**, geven we een algemene bespreking van onze voorgestelde benaderingen en bevindingen, inclusief hun beperkingen, potentiële klinische toepassingen en suggesties voor toekomstig onderzoek.

Complete List of Publications

Peer-reviewed journal publications

1. **Płotka, S.**, Grzeszczyk, M. K., Brawura-Biskupski-Samaha, R., Gutaj, P., Lipa, M., Trzciński, T., Išgum, I., Sánchez, C. I., and Sitek, A. (2023). BabyNet++: Fetal Birth Weight Prediction using Biometry Multimodal Data Acquired Less than 24 Hours Before Delivery. Computers in Biology and Medicine, 167, 107602.

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6. Sitek, A., Seliga-Siwecka, J., **Płotka, S.**, Grzeszczyk, M. K., Seliga, S., Włodarczyk, K., and Bokiniec, R. (2022). Artificial Intelligence in the Diagnosis of Necrotising Enterocolitis in Newborns. Pediatric Research, 1-6.

7. Włodarczyk, T., **Płotka, S.**, Szczepański, T., Rokita, P., Sochacki-Wójcicka, N., Wójcicki, J., Lipa, M., and Trzciński, T. (2021). Machine Learning Methods for Preterm Birth Prediction: A Review. Electronics, 10(5), 586.

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9. Payette, K., Steger, C., Licandro, R., de Dumast, P., Bran Li, H., Barkovich, M., Li, L., Dannecker, M., Chen, C., Ouyang, C., McConnell, N., Miron, A., Li, Y., Uus, A., Grigorescu, I., Ramirez Gilliland, P., Siddiquee, Md. Mahfuzur R., Xu, D., Myronenko, A., Wang, H., Huang, Z., Ye, J., Alenyà, M., Comte, V., Camara, O., Masson, J.-B., Nilsson, A., Godard, C., Mazher, M., Qayyum, A., Gao, Y., Zhou, H., Gao, S., Fu, J., Dong, G., Wang, G., Rieu, Z. H., Yang, H. S., Lee, M., **Płotka, S.**, Grzeszczyk, M. K., Sitek, A., Vargas Daza, L., Usma, S., Arbelaez, P., Lu, W., Zhang, W., Liang, J., Valabregue, R., Joshi, A. A., Nayak, K. N., Leahy, R. M., Wilhelmi, L., Dändliker, A., Ji, H., Gennari, A., Jakovčić, A., Klaić, M., Adžić, A., Marković, P., Grabarić, G., Kasprian, G., Dovjak, G., Rados, M., Vasung, L., Bach Cuadra, M., and Jakab, A. (2024). Multi-Center Fetal Brain Tissue Annotation (FeTA) Challenge 2022 Results. Submitted for publication.

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Daum, M., de Bruijne M., Depeursinge, A., Dorent, R., Egger, J., Ellis, D. G., Engelhardt, S., Ganz, M., Ghatwary, N., Girard G., Godau, P., Gupta, A., Hansen, L., Harada, K., Heinrich, M., Heller, N., Hering, A., Huaulme, A., Jannin, P., Kavur, A. E., Kodym, O., Kozubek, M., Li, J., Li, H., Ma, J., Martin-Isla, C., Menze, B., Noble, A., Oreiller, V., Padoy, N., Pati, S., Payette, K., Radsch, T., Rafael-Patino, J., Singh Bawa, V., Speidel, S., Sudre, C. H., van Wijnen, K., Wagner, M., Wei, D., Yamlahi, A., Yap, M. H., Yuan, C., Zenk, M., Zia, A., Zimmerer, D., Aydogan, D., Bhattarai, B., Bloch, L., Brungel, R., Cho, J., Choi, C., Dou, Q., Ezhov, I., Friedrich, C. M., Fuller, C., Gaire, R. R., Galdran, A., Garcia Faura, A., Grammatikopoulou, M., Hong, S., Jahanifar, M., Jang, I., Kadkhodamohammadi, A., Kang, I., Kofler, F., Kondo, S., Kuijf, H., Li, M., Luu, M., Martincic, T., Morais, P, Naser, M. A., Oliveira, B., Owen, D., Pang, S., Park, J., Park, S., **Płotka, S.**, Puyberau, E., Rajpoot, N., Ryu, K., Saeed, N., Shephard, A., Shi, P., Stepec, D., Subedi, R., Tochon, G., Torres, H. R., Urien, H., Vilaca, J. L., Wahid, K. A., Wang, H., Wang, J., Wang, L., Wang X., Wiestler, B., Wodzinski, M., Xia, F., Xie, J., Xiong, Z., Yang, S., Yang, Y., Zhao, Z., Maier-Hein, K., Jager, P. F., Kopp-Schneider, A., and Maier-Hein, L. (2023). Why Is the Winner the Best? Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pp. 19955-19966.

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8. Włodarczyk, T., **Płotka, S.**, Rokita, P., Sochacki-Wójcicka, N., Wójcicki, J., Lipa, M., and Trzciński, T. (2020). Spontaneous Preterm Birth Prediction using Convolutional Neural Networks. In Medical Ultrasound, and Preterm, Perinatal and Paediatric Image Analysis (pp. 274-283). Springer, Cham.

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Book chapters

1. Gora, P., Bankiewicz, D., Karnas, K., Kaźmierczak, W., Kutwin, M., Perkowski, P., **Płotka, S.**, Szczurek, A., and Zięba, D. (2020). On a Road to Optimal Fleet Routing Algorithms: a Gentle Introduction to the State-of-the-art. In Smart Delivery Systems (pp. 37-92). Elsevier.

Awards

1. First place in the Instrument multi-class recognition of Workflow Recognition in Endoscopic Pituitary Surgery (PitVis) as part of the EndoVis challenge during the MICCAI 2023 conference,

2. First place in the Registration task of Fetoscopic Placental Vessel Segmentation and Registration (FetReg2021) as part of the EndoVis challenge during the MICCAI 2021 conference,

3. First place in the mini-projects during the Hamlyn Winter School on Surgical Imaging and Vision, Imperial College London, 2021.

Biography

Szymon Stefan Płotka was born on December 11, 1993, in Lębork, Poland. After high school, he moved to Gdańsk and began his bachelor's studies in Biomedical Engineering with a specialization in Medical Informatics at the Gdańsk University of Technology. After obtaining his Bachelor of Engineering degree in 2017, Szymon moved to Warsaw for his Master of Engineering degree in Electronics and Computer Science in Medicine, which he earned in 2019 from the Warsaw University of Technology. His master's thesis focused on applying machine learning and deep learning methods for transvaginal ultrasound image analysis for preterm birth prediction. In 2022, he joined the interfaculty Quantitative Analysis Group embedded in the Faculty of Medicine (Department of Biomedical Engineering and Physics) and Science (Institute of Informatics) of the University of Amsterdam to pursue his PhD. During his PhD studies, he was involved in medical image analysis projects aimed at enhancing prenatal care through deep learning. He was supervised by Prof. Dr. Ir. Clara I. Sánchez (UvA), Prof. Dr. Ivana Išgum (AMC-UvA), and Dr. Arkadiusz Sitek (Harvard Medical School). He is interested in applied computer vision and deep learning-based algorithms, especially in ultrasound medical image analysis and computer-assisted interventions. Since August 28, 2021, he has been the husband of Izabela and the proud father of his beloved daughter, Amelia, since February 2, 2023.

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