Supplementary Materials: Explaining Time Series Classifier through Meaningful Perturbation and Optimisation

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Abstract

This supplementary material provides additional information and results that complement the main paper. In this work, we analyze the performance of our generative model in predicting alternative values for certain features and compare its performance with two commonly used time series imputation methods. We provide the performance of each method on adopted datasets. Additionally, we evaluate the effectiveness of our proposed framework in explaining a Temporal Convolutional Network (TCN) classifier. The code for this work is upload into https://github.com/menghan1994/ETSC_through_Meaningful_Perturbation_and_Optimisation/.

1 The performance of our model in predicting plausible values for target features

In our work, we need to generate alternative values for certain features. The aim of the generative model is to create plausible values for $\boldsymbol{x}_r^*$ conditioned by $\boldsymbol{x}_{\setminus r}^*$. This is very similar to time series imputation problems, where the missing components of time series need to be filled. However, in the missing values imputation problem, they do not have the actual ground truth value. Therefore, imputation models attempt to learn the temporal dependence of time series using observed values. The missing parts are then filled based on the learned temporal dependence. In our scenario, the time series we have are complete. We have the ground truth for each feature, so we do not need to predict them. Our goal is to generate alternative plausible values for certain features, which can maintain the perturbed time series within distribution. Nevertheless, although time series missing imputation models have a different goal, they could be applied for this. We compared the performance of various state-of-the-art missing values imputation [1, 3] and two generative methods we designed. One of the methods is based on Transformers [5], and the other is based on Bidirectional RNNs [4]. The results of these methods are shown in the following Table 1. The results shows that the Transformer-based model perform better than others.

2 The performance of our framework in explaining LSTM and TCN classifiers

In this section, the prediction accuracy of LSTM-based classifier and Temporal Convolutional Networks (TCN) [2] classifiers are provided first. Then, the deteriorate tests for these two classifiers are provided.

2.1 The predictive accuracy of these two classifiers

The accuracy of these two classifiers are shown in the Table 2.

2.2 The deteriorate tests for explanations for these two classifiers

The deteriorate tests for explanations for these two classifiers are shown in the Table 3 and Table 4. Both of these two tables shows that our method performs better than the benchmaking methods. The generative model for the Table 3 and Table 4 is Transformer-based. We also adopt the generative model

Table 1: The mean square errors in predicting values for certain features

Datasets	BRITS	E2GAN	Our Methods	
			BiRNN-based	Transformer-based
ArticularyWordRecognition	0.2891(0.0012)	0.3426(0.0007)	0.1196(0.0025)	**0.1163(0.0008)**
BasicMotions	0.1321(0.0030)	0.2079(0.0033)	0.1190(0.0031)	**0.1171(0.0018)**
CharacterTrajectories	0.1593(0.0008)	0.1812(0.0007)	**0.0375(0.0011)**	0.0959(0.0006)
Cricket	0.1242(0.0005)	0.2578(0.0008)	0.1023(0.0033)	**0.0721(0.0006)**
Epilepsy	**0.1969(0.0010)**	0.2522(0.0017)	0.2465(0.0044)	0.2230(0.0014)
ERing	0.3519(0.0011)	0.5574(0.0067)	**0.2799(0.0062)**	0.3355(0.0045)
InsectWingbeat	0.0956(0.0003)	0.0856(0.0003)	0.0752(0.0002)	**0.0557(0.0002)**
JapaneseVowels	0.3883(0.0036)	0.1826(0.0031)	0.1167(0.0018)	**0.0806(0.0010)**
Libras	0.3441(0.0072)	0.2655(0.0032)	**0.1605(0.0059)**	0.3045(0.0052)
LSST	0.1954(0.0007)	0.2046(0.0014)	0.1700(0.0011)	**0.1531(0.0006)**
NATOPS	0.1864(0.0016)	0.3306(0.0011)	0.2417(0.0014)	**0.0808(0.0004)**
PenDigits	0.4116(0.0045)	0.1333(0.0010)	**0.0706(0.0012)**	0.2985(0.0021)
PhonemeSpectra	0.1031(0.0002)	0.2308(0.0003)	0.0311(0.0000)	**0.0001(0.0000)**
RacketSports	0.1810(0.0033)	0.2165(0.0043)	0.1616(0.0034)	**0.1242(0.0019)**
SelfRegulationSCP1	0.1345(0.0012)	0.1725(0.0004)	0.1846(0.0004)	**0.1254(0.0012)**
SpokenArabicDigits	0.1765(0.0002)	0.1247(0.0003)	0.1884(0.0006)	**0.0500(0.0001)**
StandWalkJump	0.0401(0.0002)	0.0578(0.0001)	0.1075(0.0008)	**0.0352(0.0001)**
UWaveGestureLibrary	0.1598(0.0034)	0.3779(0.0012)	**0.1069(0.0050)**	0.2869(0.0010)

Table 2: The accuracy of two black-box classifiers on the adopted datasets

dataset	Accuracy		
	LSTM	TCN	Guess
ArticularyWordRecognition	**0.89**	**0.96**	0.04
BasicMotions	**0.73**	**0.83**	0.25
CharacterTrajectories	**0.67**	**0.99**	0.05
Cricket	**0.79**	**0.97**	0.08
Epilepsy	**0.54**	**0.94**	0.25
ERing	**0.79**	**0.93**	0.17
InsectWingbeat	**0.29**	**0.33**	0.10
JapaneseVowels	**0.94**	**0.91**	0.11
Libras	**0.71**	**0.69**	0.07
LSST	**0.62**	**0.64**	0.07
NATOPS	**0.86**	**0.81**	0.17
PenDigits	**0.99**	**0.97**	0.10
PhonemeSpectra	**0.14**	**0.20**	0.03
RacketSports	**0.76**	**0.77**	0.25
SpokenArabicDigits	**0.98**	**0.98**	0.10
StandWalkJump	**0.47**	0.40	0.33
UWaveGestureLibrary	**0.54**	**0.86**	0.13

based on Bidirectional RNNs to explain LSTM classifier. The result is shown in Table 5. The results in the Table 3 and Table 5 show that although the generative model based on Transformer perform better than that based on Bidirectional RNNs, it does not significantly affect the final explanation results.

Table 3: The deteriorate tests for the LSTM-based classifier (using generative model based on Transformer)

Dataset	IG	SG	LIME	LIME-G	Proposed Framework	
					with BPSO	with GA
ArticularyWordRecognition	349.00(25.75) 0.02s(0.00)	401.50(20.17) 0.01s(0.00)	645.00(38.77) 5.30s(0.43)	591.65(40.38) 9.31s(0.87)	**83.50(7.23)** 27.59s(1.43)	89.00(7.50) 34.02s(1.85)
BasicMotions	86.00(6.00) 0.02s(0.00)	465.00(26.92) 0.01s(0.00)	125.00(8.32) 6.07s(0.56)	130.70(10.04) 10.45s(0.87)	73.50(4.86) 13.45s(0.90)	**60.00(3.22)** 14.08s(0.83)
CharacterTrajectories	112.00(9.81) 0.02s(0.00)	84.50(7.63) 0.01s(0.00)	108.50(7.82) 3.73s(0.20)	93.27(6.53) 6.51s(0.58)	32.50(2.55) 23.46s(1.58)	**28.00(2.75)** 24.21s(2.28)
Cricket	8.49(0.54) 0.08s(0.01)	22.23(2.18) 0.05s(0.01)	25.62(2.02) 29.26s(2.55)	29.30(2.29) 29.90s(2.50)	12.12(1.06) 142.43s(9.82)	**8.15(0.59)** 141.92s(11.15)
Epilepsy	8.00(0.48) 0.02s(0.00)	63.50(3.36) 0.01s(0.00)	7.50(0.41) 4.39s(0.29)	6.42(0.36) 6.89s(0.53)	**4.00(0.32)** 26.41s(1.89)	5.50(0.45) 29.80s(2.94)
ERing	26.50(2.64) 0.02s(0.00)	56.50(4.49) 0.01s(0.00)	16.00(1.45) 5.63s(0.36)	14.86(1.18) 10.92s(1.09)	13.00(0.83) 17.04s(1.16)	**12.00(0.67)** 7.29s(0.72)
HandMovementDirection	70.50(4.45) 0.03s(0.00)	86.50(5.49) 0.02s(0.00)	372.00(36.72) 8.56s(0.68)	364.44(29.79) 13.16s(1.25)	72.00(6.93) 102.22s(9.21)	**34.00(2.89)** 101.71s(6.97)
InsectWingbeat	19.50(1.93) 0.02s(0.00)	65.50(4.29) 0.01s(0.00)	23.50(2.11) 8.23s(0.67)	44.00(2.56) 14.85s(0.98)	15.50(1.18) 33.10s(9.79)	**14.02(0.77)** 31.08s(1.59)
JapaneseVowels	84.00(6.08) 0.02s(0.00)	164.50(14.09) 0.00s(0.00)	101.50(6.32) 7.89s(0.43)	88.67(8.09) 10.67s(0.96)	38.50(1.99) 43.57s(3.06)	**31.00(2.73)** 12.30s(0.93)
Libras	7.50(0.54) 0.03s(0.00)	18.00(1.02) 0.00s(0.00)	8.50(0.76) 4.93s(0.25)	7.74(0.65) 7.67s(0.63)	**6.00(0.46)** 5.06s(0.30)	7.00(0.36) 4.80s(0.25)
LSST	12.50(0.95) 0.02s(0.00)	52.00(3.60) 0.01s(0.00)	10.50(0.71) 5.18s(0.49)	8.46(0.68) 8.46s(0.48)	13.00(1.23) 7.22s(0.66)	**8.00(0.74)** 6.58s(0.50)
NATOPS	446.00(42.97) 0.03s(0.00)	656.00(48.58) 0.01s(0.00)	822.50(73.36) 10.66s(1.01)	818.67(50.49) 18.98s(1.29)	**111.50(8.38)** 10.59s(1.05)	128.00(11.78) 9.04s(0.71)
PenDigits	5.00(0.47) 0.01s(0.00)	11.00(1.08) 0.01s(0.00)	5.50(0.50) 3.17s(0.25)	5.43(0.27) 4.27s(0.38)	**3.00(0.26)** 2.12s(0.17)	**3.00(0.20)** 2.27s(0.20)
PhonemeSpectra	77.00(6.94) 0.02s(0.00)	153.50(9.71) 0.01s(0.00)	562.00(120.66) 8.09s(0.57)	632.27(82.72) 15.24s(1.48)	79.00(5.19) 50.25s(4.40)	**71.00(3.69)** 46.93s(3.90)
RacketSports	34.50(1.94) 0.03s(0.00)	116.50(7.01) 0.01s(0.00)	44.00(2.26) 4.32s(0.43)	41.61(2.69) 6.54s(0.63)	25.50(1.46) 4.93s(0.28)	**20.50(1.25)** 5.16s(0.31)
SelfRegulationSCP1	16.00(1.38) 0.03s(0.00)	**3.00(0.24)** 0.02s(0.00)	**3.00(0.24)** 9.22s(0.73)	3.04(0.29) 10.47s(0.58)	**3.00(0.22)** 35.51s(3.08)	**3.00(0.22)** 38.70s(3.21)
SpokenArabicDigits	219.00(14.77) 0.02s(0.00)	935.50(75.66) 0.01s(0.00)	638.00(39.57) 4.91s(0.44)	688.94(64.33) 6.68s(0.46)	115.00(8.01) 21.41s(1.42)	**93.50(5.86)** 21.91s(1.58)
StandWalkJump	10.50(0.66) 0.08s(0.01)	25.00(1.40) 0.06s(0.00)	29.00(1.61) 32.19s(2.13)	30.58(1.81) 32.44s(1.66)	12.00(0.68) 151.23s(14.26)	**8.00(0.44)** 164.26s(14.31)
UWaveGestureLibrary	27.00(1.61) 0.02s(0.00)	29.00(1.48) 0.01s(0.00)	36.00(3.26) 4.42s(0.34)	38.26(3.65) 8.38s(0.74)	**21.00(1.81)** 52.47s(3.50)	22.50(1.23) 56.89s(3.79)
MNIST	104.00(10.06) 0.02s(0.00)	167.00(15.72) 0.00s(0.00)	90.50(8.30) 4.01s(0.30)	95.51(6.70) 7.98s(0.76)	27.50(2.36) 9.43s(0.66)	**18.00(1.56)** 10.71s(0.96)

References

[1] Wei Cao, Dong Wang, Jian Li, Hao Zhou, Lei Li, and Yitan Li. Brits: Bidirectional recurrent imputation for time series. In S. Bengio, H. Wallach, H. Larochelle, K. Grauman, N. Cesa-Bianchi, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 31. Curran Associates, Inc., 2018.

[2] Colin Lea, Michael D Flynn, Rene Vidal, Austin Reiter, and Gregory D Hager. Temporal convolutional networks for action segmentation and detection. In *proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 156–165, 2017.

Table 4: The deteriorate tests for the LSTM-based classifier (using generative model based on Transformer)

Dataset	IG	SG	LIME	LIME-G	Proposed Framework	
					with BPSO	with GA
ArticularyWordRecognition	417.82(36.27) 0.02s(0.00)	346.24(33.38) 0.01s(0.00)	547.40(31.95) 6.12s(0.57)	566.35(33.49) 9.98s(0.58)	89.93(7.81) 30.10s(1.84)	**72.53(6.66)** 38.80s(2.92)
BasicMotions	88.75(7.02) 0.02s(0.00)	536.85(29.80) 0.01s(0.00)	145.65(7.51) 6.51s(0.56)	147.71(14.08) 8.18s(0.77)	74.28(6.79) 14.44s(1.01)	**53.48(4.92)** 12.07s(1.10)
CharacterTrajectories	129.77(9.75) 0.02s(0.00)	95.07(6.60) 0.00s(0.00)	122.24(8.41) 4.40s(0.28)	89.77(8.51) 3.52s(0.30)	32.19(1.95) 22.50s(1.38)	**30.28(2.92)** 21.21s(1.93)
Cricket	9.52(0.68) 0.07s(0.01)	20.92(1.45) 0.07s(0.00)	32.01(1.97) 25.70s(1.38)	22.54(2.17) 39.45s(3.36)	9.95(0.56) 127.53s(12.51)	**8.99(0.77)** 174.16s(14.74)
Epilepsy	7.48(0.43) 0.02s(0.00)	61.32(4.78) 0.01s(0.00)	6.61(0.55) 5.02s(0.37)	8.61(0.67) 8.14s(0.48)	**3.64(0.31)** 22.94s(1.43)	5.05(0.45) 32.45s(2.54)
ERing	30.18(2.23) 0.02s(0.00)	65.10(6.30) 0.01s(0.00)	16.22(1.00) 4.78s(0.30)	15.58(1.13) 7.90s(0.67)	**13.08(0.91)** 13.66s(0.90)	13.65(0.79) 7.50s(0.41)
InsectWingbeat	19.44(1.37) 0.02s(0.00)	53.12(4.88) 0.01s(0.00)	22.36(1.34) 9.35s(0.75)	51.67(4.55) 13.61s(0.88)	15.83(1.32) 131.47s(12.26)	**12.59(1.02)** 30.92s(2.08)
JapaneseVowels	78.11(7.75) 0.01s(0.00)	175.71(8.79) 0.00s(0.00)	83.86(5.26) 6.51s(0.42)	86.43(7.47) 11.12s(0.76)	**30.95(2.13)** 38.19s(2.03)	33.49(3.32) 14.61s(0.82)
Libras	8.52(0.56) 0.03s(0.00)	19.62(1.42) 0.00s(0.00)	9.13(0.61) 5.77s(0.44)	7.58(0.72) 8.04s(0.44)	**6.48(0.44)** 5.70s(0.47)	8.01(0.53) 5.38s(0.32)
LSST	14.29(1.10) 0.02s(0.00)	52.37(4.51) 0.01s(0.00)	12.24(0.99) 5.70s(0.50)	10.44(0.81) 9.04s(0.63)	10.21(0.54) 6.20s(0.32)	**8.57(0.51)** 6.42s(0.55)
NATOPS	137.82(8.85) 0.03s(0.00)	220.16(11.83) 0.01s(0.00)	261.52(11.08) 9.04s(0.55)	198.83(16.32) 14.57s(0.74)	**100.11(8.24)** 8.85s(0.81)	114.16(9.69) 9.39s(0.62)
PenDigits	5.97(0.54) 0.01s(0.00)	13.04(0.73) 0.01s(0.00)	5.48(0.36) 3.13s(0.24)	5.42(0.28) 5.04s(0.37)	**2.72(0.25)** 1.72s(0.09)	3.28(0.23) 2.22s(0.13)
PhonemeSpectra	87.42(7.15) 0.02s(0.00)	124.94(9.87) 0.01s(0.00)	343.19(111.36) 7.70s(0.74)	270.24(88.15) 8.85s(0.53)	**67.42(7.15)** 41.59s(4.10)	88.35(8.34) 54.43s(3.17)
RacketSports	35.79(3.21) 0.03s(0.00)	134.61(9.71) 0.01s(0.00)	40.40(3.81) 3.68s(0.23)	39.86(2.79) 8.26s(0.50)	29.77(2.96) 5.04s(0.29)	**24.32(1.39)** 5.02s(0.39)
SpokenArabicDigits	228.11(18.19) 0.02s(0.00)	838.18(45.55) 0.01s(0.00)	675.55(51.41) 4.06s(0.35)	800.00(63.09) 6.04s(0.42)	129.80(8.41) 18.06s(1.17)	**110.03(10.30)** 19.16s(1.40)
StandWalkJump	8.64(0.53) 0.09s(0.01)	23.38(2.27) 0.06s(0.00)	28.68(2.73) 28.43s(2.02)	30.38(2.54) 45.44s(2.42)	14.25(1.15) 162.51s(11.19)	**7.74(0.54)** 144.43s(12.19)
UWaveGestureLibrary	31.17(2.63) 0.02s(0.00)	25.78(1.97) 0.01s(0.00)	31.99(1.63) 4.87s(0.36)	39.41(2.79) 7.92s(0.55)	**19.72(1.75)** 51.82s(4.41)	25.59(2.43) 48.40s(2.91)
MNIST	77.27(6.58) 0.02s(0.00)	175.24(10.00) 0.01s(0.00)	78.20(5.19) 3.63s(0.22)	98.64(6.95) 3.83s(0.21)	27.40(2.11) 9.33s(0.49)	**16.91(1.01)** 11.52s(1.01)

Table 5: The deteriorate tests for the LSTM-based classifier (using generative model based on Bidirectional RNNs)

Dataset	IG	SG	LIME	LIME-G	Proposed Framework	
					with BPSO	with GA
ArticularyWordRecognition	238.34(21.72) 0.02s(0.00)	273.50(20.18) 0.01s(0.00)	548.36(40.24) 6.05s(0.36)	497.19(31.88) 9.90s(0.71)	**40.32(2.17)** 29.55s(2.61)	45.84(4.10) 33.04s(2.07)
BasicMotions	82.96(6.84) 0.02s(0.00)	185.79(13.55) 0.00s(0.00)	141.53(12.00) 5.23s(0.40)	105.65(9.93) 10.32s(0.62)	63.35(1.28) 15.04s(1.07)	**60.23(5.43)** 15.00s(1.25)
CharacterTrajectories	89.47(5.25) 0.02s(0.00)	34.98(2.85) 0.00s(0.00)	97.77(8.34) 3.28s(0.20)	89.72(6.22) 7.02s(0.65)	**20.25(1.74)** 20.07s(1.74)	**24.58(0.85)** 24.87s(1.40)
Cricket	10.56(1.05) 0.09s(0.01)	21.61(1.55) 0.05s(0.00)	33.81(2.34) 25.57s(1.64)	25.22(1.73) 32.14s(2.67)	11.07(1.00) 132.82s(11.64)	**9.75(0.87)** 111.93s(10.08)
Epilepsy	4.73(0.38) 0.02s(0.00)	14.18(0.97) 0.00s(0.00)	5.35(0.51) 3.65s(0.33)	4.68(0.36) 6.92s(0.63)	**4.36(0.32)** 25.75s(1.47)	5.52(0.35) 31.38s(2.82)
ERing	28.43(1.63) 0.01s(0.00)	85.01(4.47) 0.01s(0.00)	26.52(2.18) 6.20s(0.60)	29.94(1.90) 6.56s(0.37)	**14.23(0.78)** 18.70s(1.76)	15.70(1.12) 6.35s(0.59)
HandMovementDirection	61.63(5.74) 0.03s(0.00)	84.10(7.67) 0.02s(0.00)	375.37(31.35) 9.10s(0.80)	295.83(28.32) 11.67s(0.71)	67.90(4.52) 98.82s(6.47)	**39.50(3.47)** 99.42s(6.71)
InsectWingbeat	11.92(1.07) 0.03s(0.00)	67.83(5.41) 0.01s(0.00)	28.55(2.03) 7.66s(0.70)	34.41(2.23) 11.44s(1.14)	**14.05(0.81)** 150.38s(9.26)	15.15(0.78) 34.99s(2.56)
JapaneseVowels	100.08(6.88) 0.01s(0.00)	159.33(8.78) 0.00s(0.00)	108.70(7.16) 9.10s(0.57)	63.77(3.23) 14.09s(0.86)	**28.80(0.95)** 44.48s(3.60)	29.17(1.26) 10.30s(0.80)
Libras	8.68(0.56) 0.03s(0.00)	15.15(0.93) 0.00s(0.00)	6.82(0.64) 5.26s(0.40)	8.36(0.67) 7.71s(0.44)	**6.38(0.55)** 4.63s(0.44)	7.44(0.59) 5.02s(0.35)
LSST	13.82(0.86) 0.02s(0.00)	61.27(4.90) 0.01s(0.00)	13.43(1.11) 5.26s(0.41)	15.66(0.80) 7.91s(0.67)	10.65(0.96) 7.71s(0.65)	**10.29(0.65)** 6.87s(0.39)
NATOPS	519.65(39.78) 0.03s(0.00)	779.88(68.88) 0.01s(0.00)	957.48(93.37) 11.68s(0.70)	766.71(51.25) 22.66s(1.52)	**114.63(5.86)** 11.57s(0.71)	153.03(10.60) 10.08s(0.95)
PenDigits	4.69(0.27) 0.02s(0.00)	9.98(0.59) 0.01s(0.00)	8.14(0.80) 3.80s(0.26)	7.54(0.53) 3.84s(0.32)	**4.61(0.24)** 2.42s(0.17)	5.05(0.38) 2.69s(0.15)
PhonemeSpectra	77.15(5.34) 0.02s(0.00)	160.00(15.96) 0.01s(0.00)	358.40(92.90) 7.36s(0.54)	492.48(127.21) 9.15s(0.50)	75.21(6.40) 47.55s(3.09)	**69.70(5.05)** 56.23s(5.17)
RacketSports	40.33(2.73) 0.02s(0.00)	47.25(4.43) 0.01s(0.00)	25.44(2.34) 4.84s(0.32)	22.44(1.87) 6.16s(0.56)	**10.20(0.89)** 5.34s(0.52)	11.50(0.95) 4.77s(0.32)
SelfRegulationSCP1	13.13(1.26) 0.03s(0.00)	3.05(0.20) 0.02s(0.00)	2.70(0.25) 7.77s(0.56)	3.09(0.30) 11.73s(1.12)	**2.64(0.21)** 42.39s(3.96)	3.39(0.22) 41.92s(3.50)
SpokenArabicDigits	251.69(18.27) 0.02s(0.00)	958.06(75.48) 0.01s(0.00)	563.86(32.30) 4.11s(0.41)	586.29(36.87) 7.31s(0.55)	123.00(12.28) 23.50s(1.85)	**101.43(6.92)** 24.74s(2.15)
StandWalkJump	8.87(0.82) 0.09s(0.01)	27.60(1.46) 0.05s(0.00)	29.96(1.62) 30.51s(2.70)	30.18(1.70) 51.08s(4.56)	12.13(0.78) 161.59s(15.57)	**7.27(0.71)** 175.07s(13.15)
UWaveGestureLibrary	28.59(2.31) 0.02s(0.00)	24.49(1.63) 0.01s(0.00)	36.33(3.42) 4.05s(0.25)	33.94(2.54) 8.01s(0.76)	**17.25(1.35)** 45.70s(3.07)	18.63(1.12) 61.76s(3.92)
MNIST	90.04(8.42) 0.02s(0.00)	141.76(9.01) 0.00s(0.00)	107.30(6.45) 3.72s(0.22)	115.40(9.79) 4.76s(0.26)	22.96(1.97) 10.88s(1.06)	**15.28(1.43)** 10.46s(0.64)

[3] Yonghong Luo, Ying Zhang, Xiangrui Cai, and Xiaojie Yuan. E^2gan: End-to-end generative adversarial network for multivariate time series imputation. In *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI-19*, pages 3094–3100. International Joint Conferences on Artificial Intelligence Organization, 7 2019.

[4] Mike Schuster and Kuldip K Paliwal. Bidirectional recurrent neural networks. *IEEE transactions on Signal Processing*, 45(11):2673–2681, 1997.

[5] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. Attention is all you need. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 30. Curran Associates, Inc., 2017.